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1 Graphical Abstract

2 The value pedestrians attribute to environmental information diminishes in route choice sequences

4 Yunhe Tong, Nikolai W.F. Bode

1. Mathematical model for decision-making sequences of pedestrians

$$P_x = \frac{k_\sigma \sigma_x \exp(k_f N) + k_c \frac{n_x}{n_x + n_y} + k_s S_x}{k_\sigma \sigma_x \exp(k_f N) + k_c + k_s S_x + k_s S_y}$$

2. Model validation using virtual reality experiment

3. Diminishing sensitivity to environmental information over consecutive decisions

5 Highlights

6 **The value pedestrians attribute to environmental information diminishes in route choice se-** 7 **quences**

8 Yunhe Tong, Nikolai W.F. Bode

- 9 • Pedestrians attend less to information the more route choices they make in sequence
- 10 • The effect can be formalised in a flexible mathematical model for route choice
- 11 • Implication 1: usage of a signposted shortest route may decrease in egress
- 12 • Implication 2: following may be suppressed making crowd egress more predictable

The value pedestrians attribute to environmental information diminishes in route choice sequences

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ABSTRACT

Suppose someone wants to walk from one location to another location. In doing so, they either follow a pre-planned route or decide which way to go each time they reach a junction. Research into pedestrian dynamics has carefully studied route planning and single instances of decisions on routes. However, little is known about the decision-making processes in sequences of consecutive pedestrian route choices. Here, we propose the first mathematical model for this situation. Its key hypothesis is that the sensitivity of pedestrians to environmental information, such as signs or the movement of others, diminishes, the more decisions they make in sequence. To validate our model, we conduct a virtual reality experiment with over 200 participants. Our findings suggest that sensitivity to information diminishes for the experimental case when only information on the movement of others is available to pedestrians. Comparison of our model to situations when signs are present and to data from previously published work suggests that this effect cannot be detected in short sequences of route decisions that contain three or fewer decision points. We demonstrate the implications of this diminishing sensitivity to environmental information at the example of egress from a metro-station. While the proportion of pedestrians using a sign-posted shortest route may decrease, following behaviour is also suppressed which may result in more predictable route choice dynamics across pedestrian crowds. We advocate further study on this topic in real-world settings, to investigate the need for appropriate pedestrian route choice management strategies. Our experiment also provides preliminary insights into how different personality traits affect following behaviour and we suggest this opens another avenue for future investigation.

1. Introduction

The decision making process individuals use to get from one location to another location is fundamental to research into pedestrian dynamics. This process of wayfinding or routing (Adrian et al., 2019) controls how pedestrians distribute over available routes and is therefore important for determining pedestrian densities and flows in available infrastructure. For all but the simplest routes, two extremes for how pedestrians make these decisions can be distinguished. On the one hand, pedestrians may pre-plan their route and subsequently follow this route from start to finish. This process relies on pedestrians having some form of global knowledge of their environment, and it has received wide attention in research (see e.g. Kiehl et al. (2018) for an overview). On the other hand, the route pedestrians take may emerge from a sequence of decisions, each of which is taken at a junction of roads. This process is particularly relevant for situations when pedestrians have no knowledge of the environment they are in. It is this second process that we investigate here.

The route choices pedestrians make at junctions of roads can be regarded as their integration and subsequent response to environmental information, such as signs and the movement of others, and internal information, such as prior knowledge, innate preferences or psychological state. These decisions have been studied in detail (e.g. see (Haghani and Sarvi, 2018) for a review of empirical work). Due to their ubiquity and relevance to pedestrian route choice, we focus on two sources of environmental information: signs and the movement of others.

It is generally accepted that signs are an important factor in the movement decision of pedestrians (Nilsson et al., 2009; Borowsky et al., 2008). Previous work has investigated different aspects of signage, such as its positioning, dynamic lighting, its colour scheme and the format it is displayed in, to give a few examples (Ronchi et al., 2012, 2016; Wang et al., 2006; Fu et al., 2019). Among this research there is consensus that the direction indicated by signs has a high likelihood of determining the movement decisions of pedestrians.

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The movement of other pedestrians is a type of social information that is often studied with a focus on whether pedestrians follow each other. Following behaviour can be defined as imitation behaviour or the act of following others, and it has been studied widely in simulations and experiments on crowd evacuations (Haghani et al., 2019). In contrast to the effect of signs on route choice, the evidence on following behaviour is contradictory and suggests it depends strongly on the context (for a comprehensive review, see Haghani et al. (2019)). For example, early work suggests heightened stress levels result in individuals copying each other (Helbing et al., 2000). Later work takes the more nuanced view on movement initiation that the more people someone sees leaving, the more likely they are to leave themselves and that people are less likely to move towards an emergency exit if others move in the opposite direction (Kinader et al., 2014a). Other work suggests that pedestrians prefer to exit through familiar doors even if others leave by a different door (Kinader et al., 2018). Research into crowd psychology indicates that individuals with close psychological ties will attempt to escape together during evacuations (Sime, 1983, 1995). In contrast, recent experiments conducted using crowds of volunteers found that the dominant behavior of pedestrians is to avoid others and greater stress or crowding amplifies this behavior (Haghani and Sarvi, 2019). Following behaviour can lead to an imbalanced use of exits, but some findings suggest that an imbalanced exit use actually results in pedestrians avoiding busier routes (Bode and Codling, 2013). Some work suggests that signs outweigh following tendencies (Bode et al., 2014) but this notion should not be over-interpreted, as it is likely to also depend on the context. Here, we focus on the route choice of pedestrians who are not familiar with the building they are in. Therefore, the movement of others is an important source of information and we assume individuals are more likely to follow others.

While single instances of route decisions have been investigated in detail, as discussed above, the properties of sequences consisting of many such decisions have to date not been studied. Decision making sequences are likely to occur in large and complex buildings, such as transportation hubs or shopping malls, that contain many different and long thoroughfares or evacuation routes which can force pedestrians to not only make one but many route choices.

A larger number and more complex route decisions along a path increase the cognitive load of pedestrians during the navigational process (Millonig and Schechtner, 2007). Research in psychology has found that the quality of decisions made by an individual deteriorates after a long session involving many decisions (Brocas, 2003; Inzlicht and Schmeichel, 2012). This phenomenon is sometimes called decision fatigue, a term coined by the social psychologist Roy F. Baumeister (Vohs et al., 2005). Examples for when it has been observed to occur include purchases decision of customers (Vohs et al., 2005) and parole board's decisions (Danziger et al., 2011). Considering route choice decisions in pedestrians, long routes that force people to not only make one but many decisions could potentially cause decision fatigue in pedestrians. Uncertainty over long sequences of decisions in a complex environment could increase the stress levels of pedestrians which could in turn affect their ability to perceive and process information. It has been suggested that individuals under stress are more likely to have a narrowed focuses of attention (Kowalski-Trakofler et al., 2003; Starcke and Brand, 2012), meaning they may either fail to gather the right kind of information or, alternatively, eliminate nonessential information and focus on what is most relevant. The preceding discussion of previous work in other fields of research thus suggests that the decision making process of pedestrians may change as the number of decisions they have to make consecutively increases. Establishing the existence, nature and consequences of such effects are the key research questions of our work presented here.

In this contribution, we first present a novel model for pedestrian route decisions. Informed by the work in psychology discussed above, the central hypothesis of this model is that the sensitivity of pedestrians to environmental information diminishes as the number of decisions they have to make consecutively increases. While many types of environmental information could be relevant for pedestrian route choices, we focus on signs and the movement of others. Based on previous findings for single route choices, we assume that following tendencies become stronger, the more people use a given route (Kinader et al., 2014b). The mathematical structure of our model resembles previous work in theoretical biology (Arganda et al., 2012).

We then test our central hypothesis and validate our model, via a virtual experiment that was designed to allow for long sequences of route decisions. Virtual experiments are a widely used and accepted experimental paradigm in pedestrian dynamics research, as they are cheap, safe, flexible and they permit a highly controlled setting, even though their ecological validity should be considered carefully (Lovreglio and Kinader, 2020). We test the effect of landmarks to aid orientation in our virtual building in addition to the effect of signs and information provided by the movement of others. Landmarks act as reference points that have been suggested to aid pedestrian wayfinding by identifying features in an environment and facilitating the monitoring of progress during navigation (Sorrows and Hirtle, 1999; Kettunen et al., 2013). Although landmarks did affect the behaviour of participants in our experiment, we disregard this effect in our subsequent model calibration and validation, as discussed below.

Finally, we present a case study that is inspired by the real-world setting of a metro station. We compare simulations of our model to previously published data on this setting (Lin et al., 2020) and explore the consequences diminishing sensitivity to environmental information has on the predictability of evacuation dynamics in this setting.

2. Model

Our model describes the probability of pedestrians to choose either of two possible routes, denoted x and y and we focus on situations where individuals have to make several such decisions in sequence. We assume decisions are influenced by the innate preference of individuals for either option (e.g. based on familiarity with the building) and by environmental information. As discussed in the introduction, many environmental factors can influence pedestrians' route choice. Here, we select two types of environmental information, namely signs and the movement of other pedestrians, which are generally accepted as important factors influencing the route choice of pedestrians. Extensions to include further information sources, such as the relative distance of routes, are possible but we only model such influences implicitly via the innate preferences. Aspects of the structure of our model are based on previous work on decision-making in animal groups (Arganda et al., 2012). The key novelty of our model is that we allow individuals to become less sensitive to environmental information, the more decisions they have to make.

The probability for a pedestrian to choose option x , denoted as P_x , is computed as the ratio of the evidences for the two options, D_x and D_y (the probability P_y is computed analogously):

$$P_x = \frac{D_x}{D_x + D_y} \quad (1)$$

The evidence for option x is computed as a weighted sum of the information sources and the innate preference of individuals. It is given by (analogous for y):

$$D_x = f(k_c C_x + k_s S_x) + k_\sigma \sigma_x \quad (2)$$

where σ_x quantifies the innate preference of individuals, C_x quantifies the information obtained from the movement of others and S_x indicates the presence of a sign for a route. The model parameters k_c , k_s and k_σ capture the relative weight of the corresponding information source and $f()$ is a function that implements the change in sensitivity of individuals to environmental information for consecutive decisions. We now explain each of these terms in more detail.

C_x captures the preference of pedestrians for option x , depending on how many other pedestrians have already chosen each of the options, assuming that individuals have a tendency to follow others. We implement a simple mechanism for this following tendency that is unlikely to be appropriate for all contexts but serves as an approximation of pedestrian behavior over short time intervals for low pedestrian numbers or when sightlines are uninterrupted. We do not consider issues, such as occlusion where only pedestrians visible to others are influential for route choice. Let n_x and n_y represent the number of people who have chosen options x and y , respectively. Then we define:

$$C_x = \frac{n_x}{n_x + n_y} \quad (3)$$

such that $C_x + C_y = 1$. Thus, the higher the difference in the number of pedestrians between the two options, the larger is the probability of pedestrians to choose the more popular option.

S_x is a binary variable indicating if there is a sign, such as an emergency exit sign, pointing in the direction of option x :

$$S_x = \begin{cases} 1, & \text{if there is a sign} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The innate preference of individuals for an option is a constant and $\sigma_x + \sigma_y = 1$ across the two options. Thus, $\sigma_x = \sigma_y = 0.5$ implies individuals have no preference for either option.

For the model parameters k_σ, k_c and k_s , we require $k_c + k_s + k_\sigma = 1$, to implement the weighting of environmental information sources and innate preference. As these parameters are fixed during subsequent decisions, the function $f()$ affects the balance between the innate preference and environmental information from the other pedestrians and signs.

As discussed in the introduction, we hypothesise that the more decisions pedestrians make in sequence, the less sensitive they become to environmental information. Let $k_f \geq 0$ be a parameter measuring the strength of this effect and N the number of decisions a pedestrian has already made (i.e. $N = 0, 1, 2, \dots$). Then we define the decrease in sensitivity to environmental information as follows:

$$f(a) = \frac{a}{\exp(k_f N)} \quad (5)$$

While alternative functional forms for $f()$ are possible, we suggest equation 5 provides a sufficiently general starting point.

Combining all elements of the model, P_x can be described by the following equation:

$$P_x = \frac{k_\sigma \sigma_x \exp(k_f N) + k_c \frac{n_x}{n_x + n_y} + k_s S_x}{k_\sigma \exp(k_f N) + k_c + k_s S_x + k_s S_y} \quad (6)$$

This expression can be simplified substantially and conveniently for model calibration if only a subset of information sources is relevant, as discussed below.

3. Experiments

3.1. Virtual environment

To test our hypothesis about information integration in sequences of pedestrian route choices, we conducted an experiment with human participants in a virtual environment. Participants saw a three dimensional virtual environment on a computer screen from the perspective of a pedestrian, and they could control the movement of this virtual pedestrian using the arrow keys on the keyboard to move forward and backwards, turn left and right. Before the experiment started, participants were given the option to state their age and gender. The experiment itself had two parts, followed by a short questionnaire. The first part was designed to familiarise participants with the workings of the virtual environment. In the second part, participants completed the main experimental test, a route choice task. Both parts are described in detail below. Ethical approval for our experiment was granted by the Ethics Committee of the Faculty of Engineering at the University of Bristol.

The virtual environment was implemented in Unity 3D (Version 2019.3), and the virtual pedestrian was animated using the Unity Character Pack (sample Sam, Version 2.0.0) (Unity, 2019). The walking and rotation speeds were set to 1.7m/s and 80 degrees per second, respectively. A video of the virtual environment can be found online https://uob-my.sharepoint.com/:v:/g/personal/pm19344_bristol_ac_uk/ETgOLP0BP3FP1_D9PoTE98YBiD18g0kEFycwnv_LrD3A?e=rIvj88.

In the first part of the experiment, participants were asked to complete a series of tasks, comprised of moving the virtual pedestrian in a straight line down a corridor to a designated target, returning to the starting position and subsequently finding the exit from a simple maze (for a video see https://uob-my.sharepoint.com/:v:/g/personal/pm19344_bristol_ac_uk/EWdy_jSKgT5EjAyXgWMkOHYBQA7n38fpRyjXRJsyf9uy7A?e=H6er1y). The tasks were designed to familiarise participants with the virtual environment and train them in controlling the virtual pedestrian. We recorded all movements of participants inside the virtual environment during training but did not include this in our results, because a preliminary analysis had shown that behaviour during training was uninformative for behaviour in the route choice experiment.

In the second part of the experiment, participants were inside a symmetrically hexagonal building. Participants had no knowledge of the layout of this building. Fig.1(a) shows a map of this building. It consisted of a hexagonal corridor with additional corridors that led to exits radiating off at each corner. Exits were not visible from the junctions at the corners of the hexagon, and the corridors leading towards them were the same length and displayed in the same colours as the sides of the hexagon. Initially, the virtual pedestrian controlled by the participant was placed close to a junction, but facing down the length of one of the sides of the hexagon. At the other end of this hexagon side, close to the next

191 junction were three computer-controlled pedestrians. The three computer-controlled pedestrians were animated in
 192 the same way as the participant-controlled pedestrian, and they had the same walking and rotation speeds. During the
 193 experiment their movement was simulated using Unity's navigation and path-finding tools to avoid collisions with walls
 194 and to move in a circle around the hexagon (see Appendix A for further details). Therefore, all computer-controlled
 195 pedestrians turned in the same direction at each junction. Whenever the computer-controlled pedestrians were further
 196 than one side-length of the hexagon away from the participant they stopped moving, to ensure they did not move far
 197 out of sight. Participants received the following instructions before they could start to move: "Please get out of this
 198 building". Initially, participants had to decide whether to follow the computer-simulated pedestrians or not, and if
 199 they did, they subsequently had to repeat the decision on whether to follow or not at each junction until they walked
 200 down one of the corridors to an exit when the experiment ended. For participants who decided to follow the computer-
 201 controlled pedestrians at least once, this led to a sequence of route choices. The movements of all pedestrians in the
 202 virtual environment were recorded.

203 When participants finished the second part of the experiment, they were presented with two sets of questions. The
 204 first set was a brief personality questionnaire based on the Big-Five framework, which suggests that most individual
 205 differences in human personality can be classified into five broad, empirically derived domains (openness to experi-
 206 ence, conscientiousness, extroversion, agreeableness and emotional stability) (Gosling et al., 2003). The second set
 207 of questions was designed to provide additional qualitative information on the behaviour of participants and included
 208 questions, such as what they focused on in the second part of the experiment, how easy they found it to control the
 209 pedestrian and whether they came from an English speaking country. The exact wording of these questions can be
 210 found in Fig.B.1, and free-text comments of participants are listed in Table.B.2 in the Appendix.

Figure 1: Map of the virtual environment for the main experiment (a) and still images of the virtual experiment as seen by participants on screen for the control treatment (b), the landmark treatment (c) and the sign treatment (d).

3.2. Experimental treatments

In our experiment, we tested the influence of two sources of information that are immediately relevant for the route choice of pedestrians in addition to following behaviour: landmarks and signs. A landmark is an object or feature with distinct qualities contrasting with the surrounding environment. It can be used as a reference to help pedestrians memorise or recognise routes and locate themselves relative to their ultimate destination (Sorrows and Hirtle, 1999). We have already discussed the relevance of signs to the route choice of pedestrians in the introduction.

Each participant was only allowed to take part in the experiment once and was exposed to one randomly selected treatment out of five separate treatments in the second part of the experiment. Fig.1 shows the different treatments from the perspective of participants. In the control treatment, the computer-controlled pedestrians walked in the clockwise direction around the hexagonal corridor, turning right at every junction. There were no features that distinguished different parts of the building. This treatment was designed to establish the baseline behaviour of participants in the experiment (i.e. tendency to follow others). In the anticlockwise treatment, the computer-controlled pedestrians walked in the anticlockwise direction around the hexagonal corridor. This treatment was designed to establish if participants had an innate preference for turning left or right at junctions. In the landmark and sign treatments, computer-controlled pedestrians walked in the clockwise direction, and we added features to the virtual building. Landmarks consisted of letters displayed on the walls at junctions (Fig.1c). We used the six letters (K, H, E, X, B, M) in the non-alphabetical order shown (clockwise). The sign treatment consisted of small commonly used emergency exit signs that pointed in the direction of the exit at the junctions of the hexagonal corridor (see Fig.1d). The fifth treatment, referred to as “both” for simplicity, included both signs and landmarks and computer-controlled pedestrians walked in the clockwise direction.

3.3. Data collection and analysis

We recruited participants on the campus of the University of Bristol, UK, between the 6th of February and the 12th of March 2020. Participants were not paid and only took part once. Before the experiment, participants were informed about the broad topic of the experiment and were told that they could quit the experiment at any time. No questions asked by participants were answered during the experiment to avoid providing different information across participants that might affect their decisions. To collect data from multiple participants simultaneously, we used three different laptop computers during data collection. We noticed no difference in participant experience across the different machines. The laptop models used are listed in Table.B.1 in the Appendix for completeness.

A total of 205 participants took part in our experiment. The data from seven participants had to be excluded from our analysis: one participant did not complete the questionnaire after the experiment, three lost interest and quit the experiment, and three talked with someone else during the experiment, which could have affected their decision-making. Thus the data from 198 participants were analysed, distributed across the treatments as follows: 40 participants for control, 40 participants for anticlockwise, 40 participants for landmarks, 40 participants for signs, and 38 participants for both signs and landmarks. Reported ages ranged from 18 to 45, and the median age was 21 years (12 (6%) participants did not disclose their ages). The gender distribution was approximately balanced with 99 female participants (50%), 95 male participants (48%) and 4 participants (2%) not disclosing their gender. Most participants came from English-speaking countries (142 or 71.7%). Amongst the participants who did not come from an English-speaking country, we could not discern any noticeable difficulties with understanding the meaning of instructions and concepts in this experiment.

To assess participant following behaviour quantitatively, we defined following times as the number of times a participant followed the computer-controlled pedestrians at junctions, including the initial decision before the first junction is reached. Thus, if a participant follows the computer-controlled pedestrians to the first junction and then exits, this count equals 1. For our statistical analysis of the effect of our experimental treatments and other factors on this count data, we used generalised linear models (GLMs) with a Poisson error structure and a log link function. We confirmed the appropriateness of these models by examining residual plots.

Details on how our model for sequential route choices was calibrated on this experimental data are provided after the findings of the experiment.

Figure 2: Following times for each treatment. Box and whisker plots show the median, the 25th and 75th percentiles (box) and 1.5 times the interquartile range or the maximal values in the data (whiskers). Observations beyond the whisker length are shown as outliers.

4. Results

4.1. Experimental evidence for information use

We first established what information affected the route choices of participants in our experiment, before studying our model. Figure 2 shows the following times of participants for each experimental treatment. Across all treatments, the largest number of following times we observed was 25 in the anticlockwise treatment, and some participants did not follow the computer-controlled pedestrians at all. For the sign treatment and the treatment including both signs and landmarks, most participants had following times of less than five, which was noticeably less than in other treatments. Differences between the control and anticlockwise treatment were small.

Our statistical analysis confirmed these observations (Table 1). We found that on average, participants had a tendency to follow others (non-zero intercept in Table 1), but altering the movement direction of the computer-controlled pedestrians did not reveal an inherent bias of participants to turn left or right (no effect of anticlockwise treatment, Table 1). Participants were substantially less likely to follow others when signs were present (significant negative effect of sign, Table 1). This confirms the findings from previous work on the importance of signs when compared to other sources of information in directing pedestrian route choice. Interestingly, our treatment displaying landmarks had the opposite effect to what we expected as it led to an increase in following times compared to the baseline (positive effect of landmark in Table 1). This would suggest that as different parts of the building became more distinguishable, participants followed the computer-controlled pedestrians more. As the comments by participants did not provide any qualitative explanations for this behaviour (see Table B.2 in the Appendix), we can only speculate as to why this behaviour occurred. Perhaps the different landmarks made participants curious meaning they wanted to see more of the building, or participants saw the changing landmarks as confirmation that they were following other pedestrians to new places and were thus on the right route, as there was no other information available. When landmarks and signs were present conjointly, the behaviour of participants was indistinguishable to the situation when only signs were present (Fig. 2) and we found no evidence for an interaction in the effect of the two sources of information (Likelihood-ratio test, $\chi^2_1 = 0.0332$, $p = 0.8555$). We suggest that while our findings on landmarks are interesting, further work is needed on their role in pedestrian route choice sequences. Based on these findings, we decided to not include information from landmarks into our theoretical model.

In addition to the experimental treatments, data from our personality test also helped to explain the number of times participants followed the computer-controlled pedestrians (Likelihood-ratio test, $\chi^2_5 = 22.5970$, $p = 4.0301 \times 10^{-4}$). We found that conscientiousness, the personality trait of being careful or diligent, and emotional stability, a person's ability to remain stable and balanced, both reduced the number of following times (See Table B.3 in the Appendix). None of the remaining three dimensions of personality had an effect on participant route choice. It is possible that participants with high conscientiousness scores tended to notice information that might initially be missed by others

(e.g. signs), and that participants with high emotional stability scores could handle negative emotions during the experiment such as decision fatigue and make rational choices. We suggest that these findings could provide a starting point for future investigations.

In summary, we found evidence that participants followed the computer-controlled pedestrians on average more than once (many times, in some cases) and that signs were a more influential source of information than following others.

Table 1

Statistical analysis of following times using a generalised linear model with Poisson error structure and log link function(see Appendix C for details). The response variable is the following time, a count for how many times participants followed others in the experiment. Explanatory variables are an intercept and Boolean variables indicating the presence of signs, landmarks and anticlockwise movement of computer-controlled pedestrians. P-values ≤ 0.05 are shown in bold.

Effect	Estimate	SE	F	P
Intercept	1.16327	0.088388	13.16	1.4998×10^{-39}
sign	-1.1882	0.11501	-10.331	5.0984×10^{-25}
landmark	0.28856	0.097493	2.9598	0.0030782
anticlockwise	0.10229	0.11807	0.86636	0.38629

4.2. Evidence for the diminishing sensitivity to environmental information

Having established that sequences of route choices occurred frequently in our experiment, we next calibrated our model on the experimental data and used this to test our key hypothesis on the diminishing sensitivity of pedestrians to environmental information. We used our theoretical model instead of further statistical analysis, as it easily extends to other contexts, as demonstrated below in the following section.

As we found no difference between the control and the anticlockwise treatment, we did not distinguish between these two treatments, combined their data and refer to the route taken by the computer-controlled pedestrians as option x in the following. In the absence of signs ($S_x = S_y = 0$), equation 4 for the probability of individuals to choose option x can be simplified to:

$$P_x = \frac{k_\sigma \sigma_x \exp(k_f N) + k_c}{k_\sigma \exp(k_f N) + k_c} \quad (7)$$

Making use of the requirement that the weights for different information sources add to 1 (i.e. here $k_\sigma + k_c = 1$), equation 7 can be written as:

$$P_x = \frac{(1 - k_c) \sigma_x \exp(k_f N) + k_c}{(1 - k_c) \exp(k_f N) + k_c} \quad (8)$$

Similarly, for the sign treatment P_x in our experiment, we have $S_x = 0$ (signs always indicate the alternative option y), equation 4 can be simplified as follows (making use of $k_\sigma + k_c + k_s = 1$):

$$P_x = \frac{k_\sigma \sigma_x \exp(k_f N) + k_c}{k_\sigma \exp(k_f N) + k_c + k_s} \quad (9)$$

$$P_x = \frac{(1 - k_c - k_s) \sigma_x \exp(k_f N) + k_c}{(1 - k_c - k_s) \exp(k_f N) + k_c + k_s} \quad (10)$$

Before calibrating our model on the experimental data, we used equations 8 and 10 to gain an understanding of the behaviour suggested by our model in the experiment for different parameter values. As we had no information

on innate preferences for either option, we assumed $\sigma_x = \sigma_y = 0.5$ throughout. To calculate following times, we simulated individuals who made a sequence of choices between two options based on our model until they chose not to follow the computer-controlled pedestrians. We first considered the situation in the absence of signs (see equation 8). Figure 3(a) and (b) show the effect of the two relevant parameters k_c (weighting for information to follow others) and k_f (rate of decrease in sensitivity to information) on the expected value of following times. As k_c increases, the expected value of following times increases capturing the fact that larger k_c values imply a higher weighting for adhering to information provided by the three computer-controlled pedestrians in our experiment. In contrast, as k_f increases the expected value of following times decreases, because the following behaviour diminishes faster over consecutive decisions for larger k_f . Considering the sign treatment, equation 10 shows that k_s additionally determines the route choice of individuals (weighting for information indicated by signs). Figure 3(c) shows the trade-off between the different sources of environmental information. As k_s increases relative to k_c , the expected value of following times decreases.

To calibrate our model, we assumed that the model parameters remain unchanged across experimental treatments, that is to say that any changes in participant behaviour arose from changes in the environmental information provided. Thus, we first fitted the parameters present in equation 8 (absence of signs). For the first decision, $N = 0$, which means we could determine k_c directly from the proportion of participants who chose to follow the computer-controlled pedestrians, finding $k_c = 0.78$. To determine the value of k_f , we used the data from subsequent decisions. We found that for $k_f = 1.1$ model simulations closely matched the number of following times observed in experiments (calculated as the value of k_f for which the linear interpolation between neighbouring values covered by our parameter scan in figure 3(b) was equal to the experimentally observed average following times). For the sign treatment, we then assumed that k_f remained unchanged and that the ratio between k_σ , and k_c also remained unchanged which allowed us to determine k_s in a similar way to the other parameters (i.e. the ratio $\alpha = k_\sigma/k_c$ is fixed, such that $k_s + k_c + \alpha k_c = 1$).

To validate our calibrated model and to examine our hypothesis on the diminishing sensitivity of participants to environmental information, we ran further model simulations. Figure 4(a) and (b) show the cumulative distribution function of following times for the experiment and an example simulation. These plots show a broadly similar shape, but also indicate substantial variability across simulations. Comparing the expected value (mean) of following times for model simulations with and without diminishing information in the situation without signs showed clear evidence for participants becoming less sensitive to environmental information over consecutive route decisions (figure 4(c); the model without diminishing information fails to capture the experimental data). In contrast, when signs were present, we could not determine if diminishing sensitivity to environmental information was important, because most participants followed the direction indicated by the sign at the first opportunity. Note that while it may be possible to adjust k_c in the model without diminishing information sensitivity to achieve a better fit, this would compromise the model fit for the first decision ($N = 0$).

As an additional model validation, we also compared our model simulations to our experimental data by counting the number of participants who followed the computer-controlled pedestrians above a threshold number of times (more than six times and more than once for the situations without and with signs, respectively). As for the number of following times, we found that for the situation without signs, including diminishing sensitivity to information into our model was necessary to achieve a good fit to the experimental data (figure 4(d)). The distinction for the situation with signs was similarly inconclusive as for the following times.

In summary, we found clear evidence for a diminishing sensitivity of participants to some environmental information in sequences of consecutive route choices.

4.3. Case Study

To demonstrate the flexibility of our model in applications to different contexts and to further investigate the role of diminishing sensitivity to environmental information in route choices, we compared our model to a previously published experiment (Lin et al., 2020). In this experiment, individual human participants had to exit an immersive virtual metro station via one of five available routes in the presence of computer-controlled pedestrians (see 5(a) for a diagram of routes). Crucially, the proportion of computer-controlled pedestrians using different routes was varied according to three different patterns, in which all computer-controlled pedestrians chose the same route (pattern 1), the majority of them chose the same route (pattern 2) and they split evenly across options at each decision point (pattern 3). The three patterns are shown in figure B.2 in the Appendix. We used our model from equation 6 to simulate participant behaviour for this setting considering the three patterns of crowd flow. The original study included signs pointing to all exits and for simplicity we therefore did not include any signs in our comparison, which is equivalent in our model.

Figure 3: The effect of the model parameters k_c (a), k_f (b) and k_s (c) on the expected value of following times (k_c and k_s determine the weighting of information from other pedestrians and signs, respectively; k_f determines the rate at which the sensitivity of individuals to environmental information diminishes). We show the mean following times for 1,0000 model simulations. See main text for details on model calibration. In (a) and (b), $k_f = 1.1, k_c = 0.78$ and $k_s = 0.22$ whenever the parameters are not varied. In (c) $k_f = 1.1$ and the relation between k_c and k_s is fixed (see main text).

We calibrated our model using Maximum Likelihood Estimation (MLE) on data from patterns 1 to 3 (for data and parameter estimates, see table B.4 in the Appendix). Parameters k_c ($k_s = 1 - k_c$) and k_f were constrained to be between 0 and 1 and non-negative, respectively. Figure 5(a) shows that route options in the experiment included staircases and hallways, and we therefore allowed for an innate preference σ_x for hallways in our calibration. The choice between two staircases of identical length and look was implemented as $\sigma_x = \sigma_y = 0.5$. We did not include additional information about the relative distance of route in our model, as the previous analysis had shown that participants did not select the shortest route, suggesting that other information sources were more important (Lin et al., 2020). However, for other contexts it may be necessary to include such information in our model. MLE suggested that $k_f \approx 0$. We used the Akaike Information Criterion (AIC) to compare the support of the data for our models for different values of k_f , finding $AIC = 351.5, 386.0$ and 532.7 when $k_f = 0.0, 1.1$ and 3 , respectively. These results suggest that diminishing sensitivity to environmental information was not important for the data from (Lin et al., 2020).

Figure 5(b) and (c) show that under patterns 1 and 2 in which the computer-controlled pedestrians split unevenly between two available routes at decision points, simulations without diminishing sensitivity to information ($k_f = 0$) produced a closer match to the experimental data, especially considering participants choosing route 1, the route used by most participants. One possible explanation for this finding could be that the length of the sequences of decisions (at most three decisions) was too short for the sensitivity to environmental information to diminish noticeably. However, without further data, this explanation remains speculative. In contrast to our findings for patterns 1 and 2, under pattern 3 in which the computer-controlled pedestrians split evenly at every decision point, diminishing information sensitiv-

Figure 4: Comparison of following behaviour between experiment and model simulations with or without considering diminishing information. (a) Empirical cumulative distribution function for following times for the control and anticlockwise treatments. (b) Example of a simulated cumulative distribution function for the model calibrated on the control and anticlockwise treatments. (c) Expected value of following times from simulations for the situation without and with signs and including or excluding diminishing sensitivity to environmental information. (d) Expected number of people with a following time larger than six in the absence of signs, and a following time larger than one when signs are present. The dashed horizontal lines show the experimental data. Parameters are $k_\sigma = 0.22$, $k_c = 0.78$ for (c) and $k_s = 0.85$ and $k_\sigma/k_c = 0.28$ for (d). $k_f = 1.1$ and $k_f = 0$ for the simulations with or without diminishing information, respectively. We performed the same number of model simulations as the number of participants in our experiment (control and anticlockwise treatments: 70 participants; sign treatments: 40 participants.).

ity had no substantial effect on simulations, as information from computer-controlled pedestrians did not indicate a preference for any direction and signs were not considered, see figure 5(d).

In simulations, we additionally investigated the variability in observed behaviour depending on the trade-off between different sources of environmental information and on the speed at which the sensitivity of individuals to this information diminished over consecutive decisions. We considered the same metro station scenario with two changes. First we included signs pointing exclusively along the shortest route (route 2) to an exit from the starting point, as shown in figure 5(a). Second, instead of including directional information in the form of some individuals always walking certain routes, as in the previous experiment (Lin et al., 2020), we simulated the full route choice process for 100 participants in the building who started one after the other from the same starting point. Thus, each simulated pedestrian would consider the route choices of all previous pedestrians in their decisions. We compared the proportion of pedestrians choosing route 2, the shortest route, for different values of k_s , k_c and k_f .

Figure 6 shows the distribution of these proportions over 1000 replicate simulations, each with 100 pedestrians. We consider the full distribution over replicate simulations, as the variance in global route choice outcomes is informative. The smaller the variance, the more predictable is the dynamics for a given scenario. We found that for $k_s = k_c = k_f = 0$

(a) Diagram of routes

(b) Route choices under Pattern 1

(c) Route choices under Pattern 2

(d) Route choices under Pattern 3

Figure 5: Comparison of route choices between an experiment (Lin et al., 2020) and our model for a metro station. In the experiment a single human participant had to exit the station in the presence of computer-controlled pedestrians. (a) Diagram of the possible exit routes from the starting point. The original study included signs pointing to all options. Signs are therefore not included in the simulations presented in this figure. The signs shown in (a) are considered in figure 6. (b)-(d) The proportion of individuals selecting available routes for different scenarios that vary how computer-controlled pedestrians split at the decision points. In these patterns all computer-controlled pedestrians chose the same option, route 1 (100-0 split; pattern 1), split unevenly between options favouring route 1 (80-20 split; pattern 2), or they split evenly (50-50 split; pattern 3). See main text and figure B.2 in the Appendix for details. We simulated the same number of participants as the experiment, which was 55 under pattern 1, 55 under pattern 2 and 59 under pattern 3. Dashed horizontal lines show the empirical data. Parameters used: $k_s = 0$, $k_\sigma = 0.0891$ and $k_c = 0.9109$. Values of k_f are shown in the figure.

when pedestrians had no preferences, the proportion of pedestrians choosing route 2 was around 0.25, as expected from an approximately even distribution of pedestrians over routes at each decision point. When pedestrians followed others more closely than signs ($k_s = 0.2$, $k_c = 0.7$, $k_f = 0$), the proportion of pedestrians choosing route 2 increased on

average but also became substantially less predictable (notice the large variance in proportions observed in figure 6 for these parameter values). As k_s was increased further relative to k_c , the proportion of pedestrians choosing route 2 increased further and the variability in simulation outcomes was reduced. For $k_s = 0.7$, more than 85% of pedestrians chose route 2, on average.

When introducing diminishing sensitivity to environmental information ($k_f = 3$), we found a qualitatively similar trend as the balance between k_s and k_c was altered. However, with the exception of the case $k_s = k_c = 0$, when including diminishing information, a smaller proportion of pedestrians chose route 2. This can be explained by the fact that when $k_f > 0$ in our model, the information about this exit route was considered less and less by pedestrians after each decision point. While this could be considered as detrimental to finding the shortest exit route, interestingly $k_f > 0$ also reduced the variance across simulation outcomes. This suggests that diminishing sensitivity to environmental information could in some circumstances make crowd dynamics more predictable.

Figure 6: The proportion of pedestrians choosing the shortest route, route 2, in the metro station scenario, as predicted by model simulations, when diminishing sensitivity to environmental information is present or absent. Signs point in the direction of route 2. The blue and red lines represent the route choice of pedestrians with ($k_f=3$) or without diminishing sensitivity to information ($k_f=0$), respectively. The line with circle markers indicates the baseline in which the crowd and signs have no effect on pedestrians' directional choices ($k_s=0$, $k_c=0$ and $k_\sigma=1$); the line with asterisk markers shows the situation when the movement of the crowd is highly influential ($k_s=0.2$, $k_c=0.7$ and $k_\sigma=0.1$), the line with cross markers indicates the situation when signs and crowd have an equally strong influence ($k_s=0.45$, $k_c=0.45$ and $k_\sigma=0.1$) and the line with square markers shows the situations when signs strongly influence pedestrians' route choice ($k_s=0.7$, $k_c=0.2$ and $k_\sigma=0.1$).

5. Discussion

We have formalised in a mathematical model the hypothesis that pedestrians become less sensitive to environmental information as the number of consecutive route decisions they make increases. Comparison of our model to data from a virtual experiment suggests that sensitivity to information diminishes for the case when only social information was available to pedestrians. Comparison to data from the sign treatment in our experiment and the case study (Lin et al., 2020) suggests that this effect cannot be detected in short sequences of route decisions that contain three or fewer decision points. We can only speculate on what causes this effect, taking research in Psychology and Neuroscience as starting points. One explanation could centre on the neurological processing of repetitive patterns in the hippocampus of the human brain, which has been shown to be responsible for storing a cognitive map for navigation (Dalton et al., 2015). Another explanation could take "decision fatigue" demonstrated in psychological experiments as a starting point (Brocas, 2003; Inzlicht and Schmeichel, 2012). Regardless of the precise mechanism, it is likely that the psycho-

logical state of pedestrians, such as increased stress levels, could also impact this behaviour (Kowalski-Trakofler et al., 2003; Starcke and Brand, 2012). An alternative mechanism also leading to diminishing sensitivity to environmental information over time could be increasing smoke levels in fires that limit the visual field of pedestrians.

Exactly how the sensitivity of pedestrians to environmental information changes in the course of completing a trip between two locations is therefore likely to depend on the setting and context. We have shown that the effect exists in the somewhat idealised but nevertheless plausible setting of our virtual experiment. Moreover, our simulations of the metro station demonstrate the possible implications of diminishing sensitivity to information in consecutive route decisions. On the one hand, fewer pedestrians may follow the route indicated by signs but on the other hand, following behaviour can be suppressed leading to more predictable movement patterns (following behaviour can cause unbalanced route usage based on the initial decisions of few individuals which may be subject to substantial variability).

In agreement with previous work (Bode et al., 2014), participants in our experiment were more likely to follow the direction indicated by signs than by the simulated pedestrians. Previous work suggests that the location, colour scheme, and display of signs influences the response of pedestrians to them (Ronchi et al., 2012, 2016; Wang et al., 2006). We use a commonly used exit sign design and positioned signs in prominent positions in our virtual environment which may have enhanced their effect on pedestrians. Based on previous work, our model assumes that pedestrians are more likely to follow the majority of other pedestrians at junctions of roads (Kinaterer et al., 2014b) and our successful model calibration and validation using previously published data (Lin et al., 2020) suggests this assumption is correct in the contexts we considered. This suggests a positive feedback mechanism in following behaviour in the absence of other environmental information that can lead to popular routes becoming more and more busy. However, we did not explicitly consider high pedestrian densities and resulting blockages which could deter pedestrians from following others, as previously indicated (Bode and Codling, 2013).

Our model achieves a good match to data from two separate experiments suggesting it can successfully capture pedestrian route choice across contexts. Extensions to our model that consider additional sources of information, such as light levels, pedestrian densities or road surface are possible, if needed.

The two virtual experiments we consider in this study differ substantially. The first has a simplified setting that uses symmetry to limit directional information to the signs, landmarks and crowd movement we implement. The second scenario is based on a real metro station with open spaces. We argue that it is appropriate to use the same model to explain the route choice of pedestrians in these different settings. In both experiments participants had no prior knowledge of the building and the route information shown to them was precisely controlled (i.e. signs, crowds, landmarks). Therefore, the response of pedestrians to different types of information can be investigated and our proposed model, which integrates these different information sources, can be applied in these two contexts as an approximation of the route choice mechanisms of pedestrians. More generally, the difference between the two experimental settings we consider raises the question of ecological validity, of how applicable we can expect our findings to be to real-world contexts. On the one hand, our experiment is highly controlled and abstracted and further evidence is thus needed to test if our findings generalize to real-world contexts. On the other hand, because our experiment carefully controls the information available to participant and removes extraneous information or effects, we can be certain that we have detected diminishing sensitivity to directional information, as we set out to do. We do not wish to claim that our experiment completely answers the question we pose. More work and data with higher ecological validity is needed. However, we suggest our work is a useful starting point that provides a proof of existence for the effect we investigate and, via our model, a way of making quantitative predictions that can be tested in other contexts.

The importance of landmarks for pedestrian navigation has been highlighted before (Sorrrows and Hirtle, 1999; Kettunen et al., 2013). In our experiment, the presence of landmarks increased the likelihood of pedestrians to continue following others and to remain inside the building. We have already discussed possible explanations for this behaviour. It is a limitation of our work that we cannot provide insights into the causes of this effect. Testing different types of landmarks (e.g. ones more recognisable from real buildings) and controlling the motivation of participants more carefully to avoid curiosity-driven exploration (e.g. via monetary incentives) could be informative.

We have compared our model to data from experiments in virtual environments. This experimental paradigm facilitates highly controlled data collection in large and complex buildings, which presents logistical challenges in real physical spaces. While experiments in virtual environments present opportunities and advantages, it is essential to carefully consider their ecological validity (Lovreglio and Kinaterer, 2020). In our experiment, participants were presented with an on-screen, three-dimensional environment that they could interact with via the computer keyboard. It has previously been suggested that for the type of route choices we consider here, lower levels of immersiveness than we use are adequate (Li et al., 2019). However, until more empirical evidence becomes available, there is no

guarantee that this is the case. We suggest that for our goal of demonstrating the existence of diminishing sensitivity to environmental information in sequences of route decision, experiments in virtual environments are a useful and adequate starting point.

One possible source of behavioural heterogeneity in pedestrian crowds are the different personality traits of individuals. Therefore, there is an interest to map personality traits to behaviours (Durupinar et al., 2011). For example, in crowd simulation models traits described as ‘psychoticism’ and ‘neuroticism’ are implemented as pedestrians moving past others closely in order to avoid detours and taking indirect paths to keep their distance from others, respectively (Guy et al., 2011). Similarly, in another model (Durupinar et al., 2008), the parameters controlling the movement of individuals were varied based on an assumed mapping to the Big Five personality traits (Gosling et al., 2003). We have found that participants in our experiment who reported high conscientiousness and emotional stability tended to follow the computer-controlled pedestrians less. Thus, our research provides empirical data to inform future work and to calibrate the parameter of models that investigate how personality traits influence pedestrian behaviour.

6. Conclusions

We opened this contribution by outlining two extremes of processes pedestrians could use to decide on their route to move from one location to another location. The first extreme consists of pre-planning the entire route before completing it start to finish. In the second extreme, which we investigated here, the route emerges from a sequence of consecutive decisions at road junctions. In reality, pedestrians are unlikely to adhere to either of these extremes exclusively and instead they may combine or switch between different decision making processes. Regardless of the specific mechanism, it is important to query whether the route decision process of pedestrians changes in the course of getting from one location to another location, a topic which has not received much attention to date. Our work demonstrates the existence of such changes, and our model suggests a specific mechanism for them: diminishing sensitivity to environmental information over consecutive decisions. Simulating our model suggests that the implications of changes in route decision processes could be profound. We therefore advocate further study on this topic to test for such changes in real-world settings, to measure their impact and to ultimately design appropriate pedestrian route choice management strategies.

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572 A. Navigation System in Unity

573 In Unity 3D (Version 2019.3), the computer-controlled pedestrians (‘agents’) are described as cylinders that can
 574 move within accessible areas within the virtual environment. The accessible areas are represented as a fine mesh
 575 composed of convex polygons. A path navigation algorithm controls the movement of agents on this mesh. In the
 576 algorithm, the start point and destinations of the agents are mapped to their nearest mesh polygons. Agents then
 577 compute a path on the mesh between these polygons by considering all available (i.e. unfilled) polygons. Once a path
 578 is computed, agents follow it to reach their destination. Obstacles in the path (stationary or other moving agents) are
 579 avoided by dynamically computing new paths deviating from the original path to prevent collisions. Details of this
 580 navigation system in Unity can be found online (Unity, 2019) (accessed 15 May 2020).

B. Supplementary Tables and Figures

Table B.1

Details about the laptop computers used to collect data for the virtual reality experiment.

Item	Number of participants	Details
1	65	Intel(R) Core(TM) i5-7300HQ CPU 2.50 GHz, 8.0 GB RAM
2	60	Intel(R) Core(TM) i5-7500 CPU 2.50 GHz, 8.0 GB RAM
3	58	Intel(R) Core(TM) i5-6600 CPU 2.50 GHz, 8.0 GB RAM
4	22	Intel(R) Core(TM) i7-6700 CPU 3.40 GHz, 16.0 GB RAM

Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

Disagree strongly	Disagree moderately	Disagree a little	Neither agree nor disagree	Agree a little	Agree moderately	Agree strongly
1	2	3	4	5	6	7
I see myself as:						
1. Extraverted, enthusiastic. Please select an option from the dropdown						
2. Critical, quarrelsome. 1						
3. Dependable, self-disciplined. 1						
4. Anxious, easily upset. 1						
5. Open to new experiences, complex. 1						
6. Reserved, quiet. 1						
7. Sympathetic, warm. 1						
8. Disorganized, careless. 1						

Finish and Continue

What did you focus on in the last part of the experiment (tick all that apply):

- ☐ Leave the building
- ☐ Explore the building
- ☐ Run faster than the other people
- ☐ Follow the group
- ☐ Other (please state)

Rate how easy you found it to control the player using the keyboard (from 0 (very hard) – 5 (very easy) stars)?

Are you from english speaking countries?

Quit

(a) Personality questionnaire

(b) Additional questions

Figure B.1: Screenshot of the questionnaire section at the end of the experiment.

Table B.2

Optional free-text answers recorded from participants alongside their following time. The question posed was "What did you focus on in the last part of the experiment".

Followtimes	Comments
0	'The letters on the walls and that there were not any by the exit'
1	'To not follow the majority '
1	'the purpose of this game'
1	'Follow the sign'
1	'Keep turning right'
1	'Strategy of mazes, e.g. stick left + exit signs'
1	'The exit sign on the wall'
1	'Turning left'
1	'Turn left'
1	'Understand the purpose of the introduction of people to the environment.'
1	'Go opposite direction to group'
1	'The exit sign'
1	'Tricking the system. I thought that the game wanted me to follow everyone so I did not'
1	'Not follow the group'
2	'Try to think of a bird eye view of map'
2	'Doing opposite of the group '
3	'I thought following the people might lead me to the exit, but after a couple turns, I decided maybe it was a trick, so I chose a different pathway that did not follow the other people'
3	'Followed the group for the first couple of turns but when it became clear that they were running in a circle I took my own path.'
4	'Look out for traps'
5	'At first it was to leave the group, but when I could not see a visible door I followed'
7	'I followed other players as they might also know the way out. When they looped, I explored for the exit and found it.'
9	'Memorise the letter pattern'
9	'Reading the letters on the wall/ following the group'

Table B.3

Statistical analysis of following times using a generalised linear model with Poisson error structure and log link function (see Appendix C for details). The response variable is the following time, a count for how many times participants followed others in the experiment. Explanatory variables are an intercept, Boolean variables indicating the presence of signs, landmarks and anticlockwise movement of computer-controlled pedestrians and scores for personality traits from our personality questionnaire (see B.1. Personality trait scores are computed according to (Gosling et al., 2003). The data from two questions on "Emotional stability" and "Openness to experiences" was not collected successfully. We used scores from only one question for each personality trait, namely "Anxious, easily upset(reverse)" and "Open to new experiences, complex", to represent these aspects of personality traits. P-values less than or very close to 0.05 are shown in bold.

Effect	Estimate	SE	F	P
Intercept	1.0288	0.19037	5.4045	6.498 $\times 10^{-8}$
sign	-1.1711	0.11519	-10.167	2.79 $\times 10^{-24}$
landmark	0.30395	0.098463	3.0869	0.0020223
anticlockwise	0.11555	0.1186	0.97434	0.32989
extroversion	0.0049603	0.016266	0.30494	0.76041
agreeableness	0.030828	0.022181	1.3898	0.16458
conscientiousness	-0.047719	0.016155	-2.9539	0.0031381
anxious, easily upset(reverse)	-0.071251	0.025554	-2.7882	0.052994
open to new experiences, complex	-0.012659	0.036239	-0.34931	0.72686

Figure B.2: Three patterns of routes taken by computer-controlled pedestrians, redrawn from (Lin et al., 2020). The percentages shown on arrows indicate the proportion of computer-controlled pedestrians that choose this direction at the preceding decision point.

Table B.4

Data for calibration of our model on previously published data. We show the route decisions of participants at each decision point from (Lin et al., 2020). The last column shows the parameter values of σ_x obtained from this calibration using data from all three patterns. This innate preference is only calibrated when one option is a stairway and the other a hallway (decision points 1 and 2) and set to 0.5 otherwise. We find $k_c = 0.9109$ and $k_f \approx 0$ and use maximum likelihood fitting.

Decision point	Alternative directions	Number of participants	Descriptions
Pattern 1			
Decision point 2	Hallway 2	2	0.9153
	Staircase 2	52	0.0847
Decision point 3(a)	Staircase 3	50	0.5
	Staircase 4	2	0.5
Decision point 3(b)	Staircase 3	1	0.5
	Staircase 4	0	0.5
Pattern 2			
Decision point 1	Hallway 1	52	0.9153
	Staircase 1	3	0.0847
Decision point 2	Hallway 2	16	0.9153
	Staircase 2	36	0.0847
Decision point 3(a)	Staircase 3	33	0.5
	Staircase 4	3	0.5
Decision point 3(b)	Staircase 3	2	0.5
	Staircase 4	1	0.5
Pattern 3			
Decision point 1	Hallway 1	37	0.9153
	Staircase 1	22	0.0847
Decision point 2	Hallway 2	27	0.9153
	Staircase 2	10	0.0847
Decision point 3(a)	Staircase 3	4	0.5
	Staircase 4	6	0.5
Decision point 3(b)	Staircase 3	7	0.5
	Staircase 4	15	0.5

582 C. Details of statistical models

583 The statistical models presented in Table 1 and Table B.3 are Generalized Linear Models (GLMs), a standard
584 tool in statistics (Dobson and Barnett, 2018). For completeness, we briefly explain their structure here. The models
585 seek to explain variability in a response variable y in terms of explanatory variables, x_i (where $i=1,2,3,\dots$). For
586 example, for the model presented in Table 1), there are three explanatory variables (one for the presence of signs,
587 landmarks and the anti-clockwise treatment, respectively). For our models, the response y is a count of how many times
588 participants followed the computer-controlled pedestrians. One appropriate way to model this response using a GLM
589 is to assume y follows a Poisson distribution and that the expectation of y , $E(y)$, satisfies the following relationship:
590 $\log(y) = k_0 + k_1x_1 + k_2x_2 + k_3x_3 + \dots$, where k_0 is the intercept and $k_1, k_2, k_3, \dots$ are the regression coefficients
591 corresponding to the explanatory variables. Established statistical methodology can be used to fit these models to data
592 and perform hypothesis tests on the estimated regression coefficients (Dobson and Barnett, 2018). The hypothesis tests
593 reported in Table 1 and Table B.3 all test the null hypothesis that the corresponding regression coefficient is equal to
594 zero, i.e. $H_0: k_i=0$.