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How cognitive heuristics can explain social interactions in spatial movement

Authors: Michael J. Seitz[a,b], Nikolai W. F. Bode[c], Gerta Koester[a]

Author affiliations:

[a] Department of Computer Science and Mathematics, Munich University of Applied Sciences, 80335 Munich, Germany

[b] Department of Informatics, Technische Universität München, 85748 Garching, Germany

[c] Department of Engineering Mathematics, University of Bristol, Bristol, BS8 1UB, UK

Corresponding author: Michael J. Seitz, Lothstr. 64, 80335 Munich, Germany, Phone +49 (0) 89 1265 3762, m.seitz@hm.edu

Abstract:

The movement of pedestrian crowds is a paradigmatic example for collective motion. The precise nature of individual-level behaviours underlying crowd movements has been subject to a lively debate. Here, we propose that pedestrians follow simple heuristics rooted in cognitive psychology, such as 'stop if another step would lead to a collision' or 'follow the person in front'. In other words, our paradigm explicitly models individual-level behaviour as a series of discrete decisions. We show that our cognitive heuristics produce realistic emergent crowd phenomena, such as lane formation and queuing behaviour. Based on our results, we suggest that pedestrians follow different cognitive heuristics that are selected depending on the context. This differs from the widely-used approach of capturing changes in behaviour via model parameters and leads to testable hypotheses on changes in crowd behaviour for different motivation levels. For example, we expect that rushed individuals more often evade to the side and thus display distinct emergent queue formations in front of a bottleneck. Our heuristics can be ranked according to the cognitive effort that is required to follow them. Therefore, our model establishes a direct link between behavioural responses and cognitive effort and thus facilitates a novel perspective on collective behaviour.

Keywords:

Cognitive heuristics, social interactions, collective behaviour, spatial movement, pedestrian dynamics, decision making

Introduction

How do humans respond to the social environment and make decisions based on available local information? One successful theory is based on cognitive heuristics [1,2,3]. Heuristics are simple and efficient rules that do not necessarily lead to the global optimum but yield a "good-enough solution". For instance, if you have to choose between two alternatives, you choose the one you know already rather than assessing the relative merit of both. This decision rule is called the "recognition heuristic" and there is evidence for its efficiency and use in humans [1]. In general, cognitive heuristics are *"(a) ecologically rational (i.e., they exploit structures of information in the environment), (b) founded in evolved psychological capacities such as memory and the perceptual system, (c) fast, frugal, and simple enough to operate effectively when time, knowledge, and computational might are limited, (d) precise enough to be modelled computationally, and (e) powerful enough to model both good and poor reasoning"* [2]. There is a wealth of research showing their effectiveness [3]. A good example of how simple rules may describe movement decision is given by McLeod and Dienes [4]: in baseball, fielders do not compute the trajectory of the ball and then move to that position. Instead, they may simply estimate whether the ball lands before or behind them and continuously adjust their position accordingly.

Movement in the presence of others in particular is one context where individuals have to respond to the social environment and make decisions based on local information.

Specifically, spatial movement and social interactions play an important role in the context of pedestrian dynamics. Perceptual motor-control models can be used to describe individual steering behaviour, including collision avoidance [5,6,7]. Social interactions have been successfully studied with individual-based simulation models [8,9], which typically have a set of behavioural rules or equations of motion and are studied by varying the model's parameters to explore differences in behaviour.

In social force models [10,11], 'social forces' are directly translated into physical forces, which accelerate the simulated pedestrian. Force vectors representing the various influences on the simulated pedestrian are combined (e.g. interactions with other pedestrians or preferred movement direction). To compute the motion of pedestrians, a second order differential equation has to be solved. Whether the numerical scheme necessary for this computation can be considered a cognitive capacity available to humans is questionable in our opinion. In cellular automata [12,13], pedestrians move from cell to cell on a grid. The next position is determined by either drawing from a probability distribution or optimising a utility function; both options encode social interactions and personal preferences. In the 'optimal steps model' [14], a utility function is optimised on a circle around the simulated pedestrian's current position. The radius of the circle coincides with a pedestrian's step length, thus emulating stepwise motion in continuous space. However, utility optimisation has been dismissed as an inaccurate description of cognitive processes [1]. Evaluating a probability function, as is common practice with cellular automata, does not seem to be a plausible model for human decision making either but may describe some observed crowd phenomena.

Our approach presents a departure from previous work on pedestrian behaviour in that it is based on the paradigm of cognitive heuristics. It does not rely on analogies from physics and does not contain numerical optimisation schemes. Instead, mathematical operations used for the heuristics are based on cognitive capacities that are known or can be expected to be available to humans and animals showing similar behaviour. The model is intended to not only describe behaviour but also cognition.

Particularly relevant to our study is the work by Moussaïd et al. [15,16], who proposed a process oriented perspective on decision making of pedestrians. However, while process oriented, their proposed rules lead to a numerically complex computational task. Specifically, Moussaïd and co-workers postulate that pedestrians choose the most direct path towards their target destination, taking obstacles into account. This behaviour is implemented by finding the movement direction that minimises the value of a cost function. In contrast to that, we propose rules that are computationally simple and therefore in our opinion more plausible as a description of the cognitive process. We show how very simple heuristics can be sufficient to produce plausible pedestrian dynamics.

A key novelty of our approach is that we explicitly compartmentalise behavioural responses. More specifically, we hypothesise that pedestrians follow different cognitive heuristics that are selected depending on the environment or context. This contrasts with previous work on modelling social interactions in movement in which model parameters are adjusted to reproduce or make predictions about the dynamics in different environments or contexts (e.g. [11,17]). We suggest testable hypotheses derived from our approach. To give an example, we propose a number of heuristics that represent an increase in the level of proactiveness or competitiveness of pedestrians' movement decisions. In heuristics that are more proactive or competitive, pedestrians tend to step to the side more often because they evaluate more options. The differences between these heuristics could be interpreted as context-dependent changes in social norms. Our approach facilitates a novel perspective on the behavioural responses of pedestrians. We argue that heuristics can be ordered according to the level of cognitive effort required to follow them, which may provide insights into decision making from another perspective. In some contexts, very simple heuristics are sufficient to produce plausible pedestrian dynamics, whereas in other contexts, they are not. In principle, this allows us to make predictions on the extent to which pedestrians have free cognitive capacities that they can use for other mental activities in different crowd movement scenarios. Based on these insights, built environments could be designed in a way that requires less cognitive effort and hence eases navigation for visitors.

To demonstrate the potential and usefulness of our approach, we report simulation results of two scenarios that commonly occur in real life: pedestrians moving in one direction through a narrow bottleneck, such as an exit door, and pedestrians moving in two directions in a corridor.

Methods

Simulation procedure

We represent pedestrians as disks of radius 0.2 m. Following previous work, we assume that each pedestrian has a preferred speed that is drawn from a truncated normal distribution with mean 1.34 m/s and standard deviation 0.26 m/s, truncated at 0.5 and 2.0 m/s [18]. Our model simulates pedestrian movement in discrete time and space. However, pedestrians' positions are not bound to a spatial grid and the simulation is not updated in fixed time steps. Instead, pedestrians move by making discrete steps of a fixed length at time intervals dictated by their preferred speed [19] and decide on the direction of their movement by using one of the cognitive heuristics described below. The motivation for this approach is the naturally stepwise human motion process. Additionally, there is evidence that decisions are made for each step [20]. This discretisation of pedestrian movement, albeit in combination with a utility optimisation scheme, was originally proposed with the optimal steps model [14]. Therefore, pedestrians make one decision for every step, and the step is realised in a discrete process. Additional details on the simulation procedure can be found in the supplementary information.

Cognitive heuristics for pedestrians

We implement four cognitive heuristics that simulated pedestrians use to determine the direction of their next step. Throughout, we assume that pedestrian movement is directed towards a fixed target in space (e.g. the end of a corridor or an exit). Therefore, the default movement preference of pedestrians is directly towards a target [21] in all four heuristics. Targets are implemented as rectangular surfaces inside the simulated environment and pedestrians attempt to move in a direct line from their current position to the nearest point on this surface. When pedestrians reach an intermediate target, they are assigned the next target and when they reach their final target, they are removed from the simulation. Our cognitive heuristics implement this goal-directed movement, as well as the responses of pedestrians to their environment (figure 1).

The *step or wait heuristic* describes the most basic movement behaviour that avoids collisions (fig. 2a). Pedestrians assess if a step from their current location in the direction towards their target leads to a collision. If not, they take the step. Otherwise, they remain stationary. We define collisions to occur if the pedestrian's body overlaps with the body of another pedestrian or a wall at any point on the path between their current location and the location one step length directly towards their target. The only cognitive capacities necessary for this heuristic are the anticipation of the next step towards the target (for the neural basis of this capacity, see [22]) and the detection of a collision on the path to it (e.g. [23,5]).

With the *tangential evasion heuristic,* pedestrians first assess a step directly towards their target. If this leads to a collision, they assess if they can make either of the two steps that tangentially avoid the closest pedestrian between them and the target, starting with the step that gets them closer to the target (see [24,25] for the estimation of distances). Only if both of these steps also lead to a collision, they remain at the current position (fig. 2b). The only additional computations necessary for this heuristic are finding the tangential evasion points and estimating the distance to the target. In our simulations, these points are determined by moving one step length along the tangents from the moving pedestrian's centre to a circle around the centre of the pedestrian in their way. This circle has a diameter of two pedestrian diameters, which avoids overlapping of the physical representations of pedestrians. This heuristic contains the step or wait heuristic and adds further planning, making it more demanding. We also suggest that since pedestrians evaluate more options in this heuristic when compared to the step or wait heuristic, it is a more proactive or competitive heuristic that pedestrians employ when their level of motivation to reach the target is higher. Specifically, by evading to the side pedestrians tend to overtake others in front of them.

The *sideways evasion heuristic* extends the tangential evasion heuristic and is therefore more demanding than the previous two heuristics. If tangential evasion steps are not possible, pedestrians additionally consider evasion steps orthogonal to the direct line towards the target, starting with the step that gets them closer to the target. Only if all of these steps lead to a collision, the pedestrian remains at the current position (supplementary figure S1).The sideways evasion heuristic comprises the evaluations of the previous heuristics. Therefore, we suggest that the sideways evasion heuristic is more proactive and competitive than the tangential evasion heuristic. Behavioural rules similar to the sideways and the tangential evasion heuristics have been implemented previously [26]. However, this implementation in a cellular automaton was not motivated through cognitive heuristics and was not compared to empirical data.

In dense crowds, pedestrians may use the same path chosen by another pedestrian walking in the same direction [27]. This is captured in the *follower heuristic* (supplementary figure S2). If agents detect a collision with someone walking in the opposite direction on the path to the target some steps ahead, they start following the closest pedestrian moving in the same direction. If that fails, they use the sideways evasion heuristic to navigate directly to the target. Collisions are detected by extending the direction to the target by 5 steps. To account for pedestrians walking in the same direction, crossing paths are only considered a collision if the other pedestrian's last movement direction has an angle greater than 2/3 π radians to the target direction of the focal pedestrian. In that case, a pedestrian to follow is searched for within a 10 m radius. This pedestrian must be within a range of π/2 radians relative to the current walking direction of the focal pedestrian. Furthermore, the walking directions of the two pedestrians must not differ by more than π/2 radians. While it is possible to change the parameters of this heuristic (e.g. searching radius), we focus on conceptual ideas and the general plausibility of heuristics and therefore keep parameter values fixed.

The follower heuristic assumes the capacity to anticipate the own movement towards the target and detect collisions on this path, and to locate another individual moving in the same direction (see [21,28] for details on motion perception). Additionally, it contains the computational steps of the previously defined heuristics. Therefore, this heuristic is potentially more demanding than the other three, but may also be less demanding if following another pedestrian prevents tangential or sideways evasions. In contrast to the previous heuristics, which can be ordered in terms of increasing levels of proactiveness or competitiveness, the follower heuristics presents a departure from this concept. Being a forward-planning strategy, which pedestrians may employ to facilitate their progress within a crowd, it is certainly proactive. However, this strategy should not be related directly to pedestrians being competitive, as it involves following and therefore accepting not to overtake others, who move in the same direction.

Pedestrian decisions in our model are essentially deterministic. Stochasticity is introduced in the simulations only through the pedestrians’ preferred speeds, initial conditions (e.g. positions of pedestrians), and the random resolution of conflicts in the order of movement events. Once the general model parameters (pedestrian radius, preferred speeds, initial conditions) have been set, the simulation proceeds according to the deterministic cognitive heuristics. The heuristics we propose do not allow pedestrian to step backwards. Instead, conflicts are resolved by evading tangentially, to the side, or by following another pedestrian ahead. If two evasion directions around a conflict position yield equal progress towards the target, one is chosen at random. Cultural norms may result in a preference for evasions to the left or right around conflict positions (e.g. [17]) and it would be possible to include such preferences in our model. We aim to model general behaviour and therefore do not implement side preferences. Nevertheless, such preferences may have an impact on crowd dynamics and should be introduced and calibrated according to measurements when scenarios in specific contexts are studied.

Our model has been designed deliberately to be a modular framework of heuristics that can easily be extended with additional behaviours. This is illustrated by the construction of new heuristics by including other heuristics and is in line with the notion of a heuristic toolbox [1]. Furthermore, a similar approach has been successfully applied in robotics [29]. The modularity not only allows for the incremental construction of behavioural rules but also facilitates extending the model to describe additional behavioural features. As discussed below, the flexibility may represent a challenge in model validation. However, we also argue that this paradigm is plausible for evolved biological behaviour [1].

In the results and discussion section, we use the terms cognitive effort and cognitive capacity. Cognitive effort is defined through the (explicitly stated) computational steps necessary for the decision. A cognitive capacity is a computational step in a heuristic. An additional discussion on the justification of the approach with cognitive heuristics can be found in the supplementary information.

Bottleneck simulations

We simulate pedestrians exiting a room (width 14 m, length 11 m) through a narrow bottleneck (width 2 m, length 5 m). We position an intermediate target at the entrance to the bottleneck and the final target at the end of the bottleneck (both targets are quadratic boxes, side length: 1.4 m). At the start of simulations, 180 pedestrians are randomly distributed 8 m in front of the bottleneck entrance inside a box of width 10 m and length 5 m (see also fig.

3a.1-c.1). The size of the room, bottleneck, and crowd are similar to the setup of an experiment with volunteers [30]. We can therefore compare the output of our simulations directly to experimental data. The experimental data comprises the trajectories of 179 pedestrians exiting through the bottleneck in one run, and we compare this data to 10 replicate simulations each for the step and wait, tangential, and sideways evasion heuristics.

We use a summary statistic to quantify pedestrian movement in the bottleneck scenario (more details can be found in the supplement). This measure takes high values when the queue is spread out along the width of the room in front of the bottleneck and low values for long and narrow queues. Changes in this measure over time and across heuristics provide insights into the form and stability of pedestrian queues.

Corridor simulations

We simulate pedestrians moving in both directions through a 48 m long and 6 m wide corridor. Pedestrians are introduced into the corridor by being placed at a random location inside a box (width 5 m, length 2 m) at either end of the corridor. One additional pedestrian is introduced into the scenario at a fixed rate, every 0.5, 1.0 or 2.0 seconds, on both sides of the corridor. Once introduced into the corridor, pedestrians move towards a target that spans the entire width at the opposite end of the corridor. The target is located 1.5 m in front of the box in which pedestrians walking in the opposite direction are introduced into the corridor (see fig. 4a.1 for environment layout). We run simulations for 300 s and stop introducing new pedestrians after 250 s. We compare the results for 10 replicate simulations for each of our four cognitive heuristics.

To compare the rate and efficiency at which pedestrians move through the corridor across heuristics, we report the flow computed as the number of pedestrians that cross the halfway mark through the corridor in either direction in 1 s. With this measure (more details can be found in the supplement), we quantify the extent to which pedestrians form lanes, an emergent phenomenon observed in empirical data that has also been reproduced in computer simulations [10].

Results and discussion

To start with, we show that our heuristics produce plausible pedestrian dynamics in a bottleneck scenario (figure 3). The simulation snapshots already indicate differences in the dynamics between heuristics. The step or wait heuristic (fig. 3 a.1) produces a cone-shaped agglomeration in front of the bottleneck. The tangential evasion heuristic (fig. 3 b.1) leads to a more compact, rounded queue, and the sideways evasion heuristic (fig. 3 c.1) produces a semi-circular queue. Although the limited field of view and camera distortion make it difficult to see, it appears as if the experimental data (fig. 3 d.1) is closest to the tangential evasion heuristic. The results for the follower heuristic were similar to the sideways evasion heuristic (supplementary figure S5) because pedestrians adopting the follower heuristic revert to the sideways evasion heuristic in the case of jamming.

The queue measure clearly illustrates differences between the three heuristics. The step or wait heuristic (fig. 3 a.2) yields the smallest values for the measure capturing the fact that queues produced by this heuristic are elongated and do not utilise the width of the available space in front of the bottleneck (see fig 3 a.1). For this heuristic, the pedestrian crowd also takes the longest to exit the room. The tangential evasion heuristic (fig. 3 b.2) leads to higher queue measure values and the egress time is considerably faster. The sideways evasion heuristic (fig. 3 c.2) results in even higher values for the queue measure, capturing the fact that queues are wide (fig. 3 c.1). Interestingly, this heuristic does not lead to faster egress. For the step or wait heuristic, the tangential evasion heuristic and the experiment, the queue measure attains a roughly stable value shortly after the start until just before the end of simulations. For the sideways evasion heuristic, this stable regime is either much shorter or does not exist. Across the three heuristics, the tangential evasion heuristic matches the empirical data (fig. 3 d.2) best.

Next, we investigate the steps pedestrians actually performed in simulations (e.g. sideways or forward step). We verify that the respective heuristics lead to different behaviour and reveals how the behaviour changes over time (fig. 3 a.3-d.3). For all heuristics, the dominant behaviour over most of the time is to remain at the current position because of the congestion in front of the bottleneck. At the beginning and increasingly towards the end, the less congested state of the crowd allows for both steps forward and evasion steps. The density-speed diagrams show that, in contrast to the experiment, heuristics do not reach densities higher than 5 pedestrians/m^2 (supplementary figure S6 a-d). This can be explained by the fact that pedestrians in the simulation do not close gaps in front of them when the gaps are smaller than their preferred step length. However, the general shape of the density-speed diagram produced by the simulations is comparable to the experimental data.

Taken together, these results show that while all heuristics produce plausible pedestrian dynamics, simulations of the tangential evasion heuristic are the most similar to the experimental data. However, we suggest that in other contexts, different heuristics may be more relevant. When describing our heuristics for pedestrians, we have already introduced the notion that some heuristics capture more proactive or competitive behaviour. This suggests a testable hypothesis arising from our simulations. In situations when social norms or the context demand a high degree of cooperation or courtesy or when people are not rushed, they may use the step or wait or tangential evasion heuristic and we thus predict behaviour similar to the dynamics observed in simulations of these heuristics. These heuristics require fewer computations and are therefore less demanding cognitively. If pedestrians attempt to reduce their cognitive effort [31] this may be their default behaviour. In situations when people are highly motivated to pass through a bottleneck quickly (e.g. during stressful evacuations), they may use the sideways evasion heuristic and thus we predicts longer detours in order to overtake others. There is qualitative evidence on the shape of queues supporting this hypothesis from an experiment in which the motivation of volunteers to walk through a bottleneck was controlled carefully [32]. In contrast to previous work where different motivation levels were captured by adjusting model parameters (e.g. [11]), we suggest that changes in motivation lead to the adoption of different heuristics.

To investigate how crowd dynamics are affected by the use of different heuristics over time, we consider four combinations of heuristics in the bottleneck scenario (fig. 4). First, we randomly assign heuristics to pedestrians with equal probability at the start of simulations. Second, we let pedestrian randomly choose one of the heuristics for each step with equal probability. Third, pedestrians try to evade tangentially after having remained at one position 3 times and try to evade to the side after having remained 5 times. Once they have moved, they revert back to the step or wait heuristic. Fourth, instead of reverting to the step or wait heuristic as in the third scenario, pedestrians continue to follow the respective evasion heuristic after having used it for the first time. We chose these examples to illustrate how different ways of selecting heuristics affect the collective dynamics and to explore if individuals who follow different heuristic exit faster or slower than others.

We report the percentage of each heuristic used over time (fig. 4 e-h.1), the queue measure (fig. 4 e-h.2), and percentage of the observed stepping behaviours (fig. 4 e-h.3). With the random distribution of heuristics, pedestrians following the tangential or sideways evasion heuristics exit earlier than pedestrians following the step or wait heuristic (fig. 4 e.1). These simulations produce a peak in the queue measure at the start of simulations (fig. 4 e.2). The peak indicates that a broader queue shape forms, which subsequently dissolves before pedestrians following the step or wait heuristic leave the scenario (fig. 4 e.3). When pedestrians randomly select their heuristic strategy for each step with equal probability (fig. 4 f.1-3), evacuation times do not differ greatly from the tangential evasion heuristic (fig. 3 b.1-3). In the third scenario, where pedestrians choose a more competitive strategy after remaining at the same position for some time (fig. 4 g.1-3), the congestion builds up more slowly but finally reaches the same values as in the previous scenario (fig. 4 g.2).

Pedestrians most often chose the sideways evasion heuristic between 30 to 60 s (fig. 4 g.1). However, this does not result in frequent sidesteps, as they mostly have to remain at the current position (fig. 4 g.3). In the fourth scenario, when pedestrians switch to a more competitive heuristic after remaining at one position for some time and then keep using this heuristic (fig. 4 h.1-3), the sideways evasion heuristic increasingly dominates the other heuristics (fig. 4 h.1). Here, the egress times are shortest and similar to the tangential and sideways evasion heuristic (fig. 3 b and c). The queue measure (fig. 4 h.2) increases until it peaks at around 40 s with an equally high value as the sideways evasion heuristic (fig. 3 c.2). Interestingly, the step or wait heuristic dominating at the beginning does not lead to an increase in overall egress times.

We derive additional hypotheses from these results. Pedestrians who evade sometimes after remaining at a position (fig. 4 g.1-3) do not seem to have an advantage compared to not evading at all (fig. 3 a.1-3). Nevertheless, switching to a more competitive behaviour (fig. 4 h.1-3) seems to lead to the most efficient egress, that is, being cooperative first and then competitive does not seem to have a disadvantage over being competitive from the beginning. This suggests that it may be most efficient to first follow a cooperative strategy with less cognitive effort and only switch to a competitive one if cooperation fails instead of being competitive from the beginning (fig. 4 h.1-3). When there are cooperative and competitive individuals in the crowd (fig. 4 e.1-3), the competitive individuals have a clear advantage as they exit first, but there is no great difference between the tangential and sideways evasion heuristic. The less competitive individuals also seem to benefit from the competitiveness of others because the overall egress time decreased compared to full cooperation (fig. 3 a.1-3). When available, sideways evasion is rather rare (fig. 3 c.3 and fig. 4 h.3) but does have a considerable impact on the queue measure. Tangential evasion seems to be the preferred choice for intermediate congestion states as it peaks twice, at the beginning and towards the end, when all evasion options are available. As our findings depend on how exactly pedestrians select the heuristic they follow, we provide a useful illustrative indication of the implications of these dynamics.

We now investigate if our heuristics also provide plausible dynamics in the second scenario, bi-directional flow in a corridor (figure 5). The snapshots give an indication for the differences in dynamics between heuristics. The step or wait heuristic (fig. 5 a.1) produces a global jam and poor usage of space (pedestrians are not evenly distributed in the available space). The tangential evasion heuristic (fig. 5 b.1) and follower heuristic (fig. 5 d.1) lead to a more even distribution of pedestrians in space, but local jams still appear. The sideways evasion heuristic (fig. 5 c.1) produces the most even distribution of pedestrians in space, and no jams are visible in the corridor for this simulation. The follower heuristic is the only heuristic for which the snapshot gives an indication of lane formation. However, pedestrians walking in opposite directions still encounter each other on both sides, that is, the two walking directions are not separated into constant stable lanes.

The flow of pedestrians over time confirms these qualitative observation (fig. 5 a-d.2). In simulations with the step or wait heuristic, no steady flow of pedestrians through the corridor can be established. As pedestrians with this heuristic lack the ability to walk around oncoming pedestrians, it inevitably leads to a jam of pedestrians in the corridor (fig. 5 a.2). Although this heuristic leads to plausible crowd movement in the bottleneck scenario, in a scenario with pedestrians walking in opposite directions, it is not appropriate. In simulations with the remaining three heuristics, we can observe a constant flow of pedestrians in the corridor for low pedestrian densities (delays 1.0 and 1.5 s). At the start of the simulations, there is a transient time before a constant flow is established, and at the end of simulations, the flow decreases with the number of pedestrians still inside the corridor. However, for higher densities (delay 0.5 s), the tangential evasion and the follower heuristic sometimes fail to sustain a flow of pedestrians through the corridor. The flow initially reaches a high level, but then decreased as local jams occur, spread and gradually make the corridor impassable.

Only the sideways evasion heuristic leads to a constant flow of pedestrians at the highest rate entrance rate of pedestrians (with the exception of one run). This suggests that the tangential evasion and the follower heuristic may only apply to particular contexts (certain pedestrian densities in this case). For higher densities, a different strategy is necessary.

It is a well-documented phenomenon that pedestrians form lanes by walking behind one another in dense crowds [33,27]. We found that evidence for lane formation was not very pronounced for all heuristics apart from the follower heuristic. Here, a strong, spatially localised tendency of pedestrians walking in the same direction when crossing the halfway line emerged over time (movement direction measure; fig. 5 a-d.3 and supplementary table S8). Therefore, if we take the emergence of lanes as the criterion for a plausible pedestrian model, we have to conclude that only the follower heuristic is appropriate in this context. Previously developed simulation models have also succeeded in producing lanes in pedestrian crowds. However, simulations with these models typically implement periodic boundary conditions by connecting the two ends of the corridor and have to run simulations for some time before stable lanes are formed [10].

Although experiments with volunteers on pedestrians moving in corridors have been conducted [33,8,27], a direct comparison to simulations is difficult. In experiments, participants typically enter a corridor segment centrally at one end and leave at the sides on the opposite end [34]. Individual-level target choice (i.e. which side to exit on) and forward-planning (e.g. participants observe the establishment of a convention of keeping left/right) would require additional modelling steps implementing individual decision-making to meaningfully compare pedestrian simulations to such experiments. Therefore, a comprehensive comparison of our heuristics to empirical data is beyond the scope of this work.

The two simulation studies suggest that some heuristics are more plausible than others depending on the context. The step or wait heuristic produced plausible emergent behaviour in the bottleneck scenario but failed to resolve most basic conflicts in the corridor scenario. The sideways evasion heuristic both allowed for egress through a bottleneck as well as counter flow without jamming. However, it did not produce lanes in the pedestrian flow. The follower heuristic was not able to always prevent jams in the corridor but did produce lanes. In general, we suggest that heuristics are selected depending on the context. This is the crucial difference of our approach compared to most previous modelling frameworks. Instead of formulating one model that attempts to describe all aspects of pedestrian dynamics with changes in model parameters, we suggest that there is a collection of heuristics that are only activated if they are chosen for a specific task based on cues from the environment [3].

Table 1 summarises the cognitive heuristics we propose and their respective different levels of cognitive effort. Our simulations demonstrate that some heuristics can adequately describe pedestrian dynamics in some situations but that the same heuristics are inadequate for other situations (e.g. step and wait heuristic can describe queuing at exit, but not bi-directional flow in a corridor). Based on this, we suggest that some situations impose a higher cognitive demand on pedestrians. This hypothesis could be tested experimentally. For instance, exposing pedestrians to such situations and measuring their performance in a separate task to be accomplished at the same time (e.g. a counting task) could reveal how much cognitive effort can be diverted away from walking in the presence of others. Previous work has already shown such effects in individuals moving in the absence of others [35].

Conclusions and future directions

We proposed four cognitive heuristics that describe and can be used to simulate pedestrian behaviour (summarised in table 1). The heuristics are modular, can contain each other, and therefore vary in degree of complexity. Their computational steps are based on the cognitive capacities of humans. Hence, they are plausible hypotheses for the human decision making process and a step towards explaining social interactions in spatial movement. We used simulations to study emergent effects in two scenarios: egress through a bottleneck and bi-directional flow in a corridor. We validated our results for the former scenario by comparing simulations to a controlled experiment. The simulation results demonstrated how different heuristics lead to different group-level dynamics and we argued that a collection of heuristics is necessary to describe human behaviour for local navigation tasks. Our approach to simulating pedestrian dynamics is fundamentally different to previous models since it allows for the direct study of cognitive processes. We suggest that heuristics can help to explain the cognitive effort connected to moving in a social environment depending on the context. Additionally, we hypothesise that the motivation of pedestrians to move faster could influence the choice of heuristics.

In order to draw conclusions from our model, it has to be tested against empirical observations. This poses a challenge since it is not clear when a proposed heuristic is a valid model. We argue that the simplest cognitive heuristic that can reproduce an emergent effect is the best model. This argument is supported by the principle of parsimony [36], and we additionally argue that biological organisms economise on energy consumption and hence cognitive efficiency due to evolutionary pressure. Furthermore, free cognitive capacities allow for the coordination of other mental activities and hence give an additionally evolutionary advantage.

If one heuristic has been found to be inadequate for the description of some phenomenon, this does not mean the paradigm of cognitive heuristics is wrong. It may simply be the wrong heuristic for the context under consideration. At first glance this presents a potential challenge to the paradigm: it appears to allow for new heuristics for every possible novel context. To a certain extent this is plausible, as humans are likely to use a large number of cognitive heuristics [1]. However, the cognitive abilities of humans present a natural limit to the number and nature of cognitive heuristics that can be considered in our approach.

Furthermore, as more heuristics for pedestrian behaviour are developed, the usefulness of each heuristic has to be re-assessed according to the parsimonious principle outlined above. Therefore, selecting or detecting which heuristics are actually used is a key challenge in future model development. One consistent approach could be to find heuristics for the selection process. Another approach could be to use unsupervised learning methods from machines learning (e.g. [37]) to discover basic behavioural building blocks. Although large data sets are necessary for this, with technologies on the rise that allow for cheap recording of pedestrian motion and at the same time ensure anonymity and data protection (e.g. [38]), it seems feasibly to conduct such research.

The explicit modelling of cognitive heuristics or rules of thumb for pedestrian dynamics has practical advantages: the description of heuristics can be given in general language and the resulting models can therefore be used more easily by experts from fields other than mathematical modelling. Although technical knowledge may be necessary for algorithmic implementations, new heuristics can be proposed by a wide community. Furthermore, tools could be developed that allow for the combination and the testing of cognitive heuristics without technical knowledge about the precise mathematical computation.

In our simulation model, we have focused on an initial development of cognitive heuristics for pedestrians and on demonstrating the usefulness of this approach. Many extensions to our model are possible and may even be necessary. We have already mentioned that additional heuristics will have to be developed to capture the decision making of pedestrians in different contexts. For example, structured social interactions (e.g. with friends or family; [39]) could result in the introduction of compromise decisions in heuristics. Staying close to family members or friends may stand in contrast to moving quickly through a narrow bottleneck. In such situations, a compromise has to be found, which can be realised by linearly combining terms for different objectives [6]. Another aspect of pedestrian behaviour that naturally entails some compromise is walking around a corner. Usually humans want to keep a certain distance to walls. This stands in contrast to passing around the corner on the shortest path. Pedestrians may accept getting very close to the wall directly at the corner but keep a greater distance otherwise [40].

Our cognitive heuristics only capture the movement decisions of pedestrians. To account for microscopic aspects of movement that are based on physical (e.g. collisions) or biomechanical properties (e.g. locomotion, gait), a continuous motion process is necessary. Our heuristics-based decision process could be complemented with a physical layer. Decisions could be passed on to a physical or biomechanical model that executes the resulting movement. An advantage of this extension would be that phenomena based on physical contact, such as shock waves in crowds [15], could be simulated along with a plausible psychological decision process. The discrete stepping process and additional heuristics could be used to investigate macroscopic features of pedestrian flow through microscopic simulation and help to test assumptions about the underlying mechanisms. For example, Johansson [41] proposed that the distance pedestrians keep to others in front could be related to their stepping behaviour. He showed how this distance and the variation in speeds between individuals can determine the density-speed relation.

Modelling pedestrian behaviour with cognitive heuristics opens up links in many directions. Therefore, our approach may inspire researchers from many fields to use a similar approach to study questions in their domain. Given the same paradigm, findings can also be integrated and used across disciplines. Therefore, our model could be the start of a new line of research studying social interactions.

Ethical statement

No experiments with humans or animals were conducted for this research. The empirical data used had been published before and is cited accordingly.

Competing interests

We have no competing interests.

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Authors’ contributions

MJS and NWFB designed the study; MJS, NWFB, and GK analysed and interpreted the data. MJS conceived of the simulation model, designed and implemented the simulation procedures, carried out the simulation study and statistical analysis; MJS and NWFB drafted the article; MJS, NWFB, and GK critically revised the article and gave final approval for publication.

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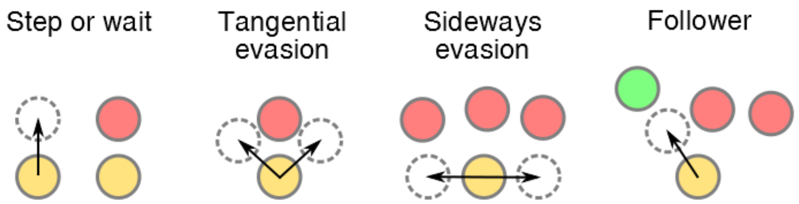

Figure 1: Illustration of behaviours with the four heuristics. The focal pedestrian is the lower, filled (yellow) circle; the solid circles on top are other pedestrians; and the dashed circle represent possible movement steps with the respective heuristics. In all cases, pedestrians try to move towards the top. With the step or wait heuristic, pedestrians either take the step or wait if the position is already taken. With the tangential evasion heuristic, pedestrians choose steps to the side of the conflicting other pedestrian. With the sideways evasion heuristic, pedestrians move to their own side with respect to the target if the path is blocked. With the follower heuristic, they try to follow another pedestrian walking in the same direction (here, to the upper left, in green).

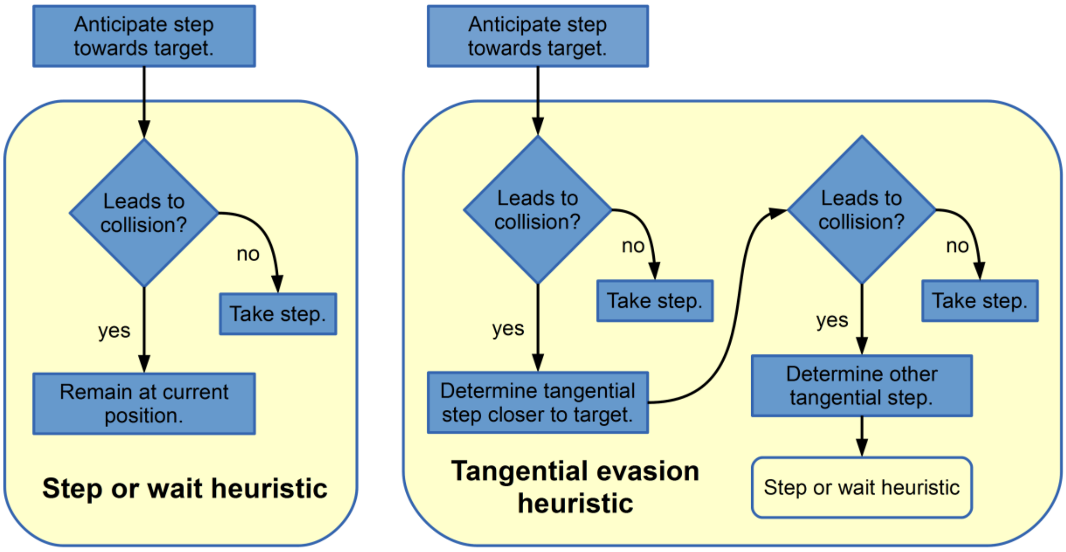

Figure 2: Basic cognitive heuristics for pedestrian decision making. We show the ‘step or wait heuristic’ on the left and the ‘tangential evasion heuristic’ on the right. Each computational step represents a cognitive capacity that has to be available. Heuristics are shown in (yellow) boxes with rounded corners. Rectangles (in blue) show actions or calculations of pedestrians and (blue) diamonds show binary decisions. Rectangles with round corners (in yellow) show whole heuristic

building blocks, which can appear in other heuristics. For example, the tangential evasion heuristic contains the step or wait heuristic and therefore has higher cognitive demand.

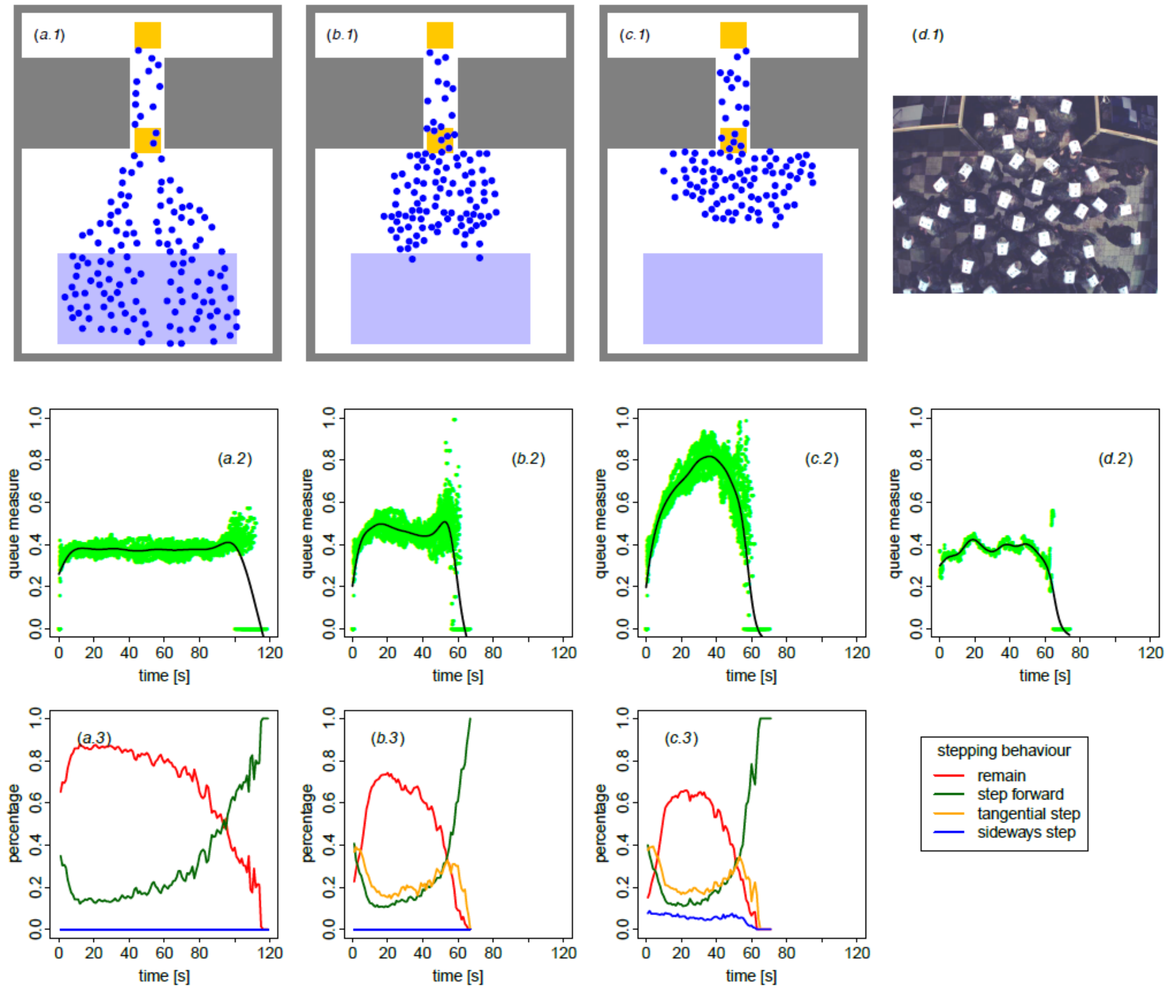

Figure 3: Analysis of an egress scenario with the step or wait heuristic (a.1-3), tangential evasion heuristic (b.1-3), sideways evasion heuristic (c1-3), and the results from a controlled experiment (supplementary material and methods, [29]) with a similar experimental design (d.1-3). The snapshots in the first row were taken 30 s after the start of the first simulation run (a.1-c.1) and 30 s after the start of the experiment (d.1; still image of experiment reproduced with permission of the authors in [28,29]). The camera distortion visible in d.1 was corrected in the experimental data analysed in d.2-3. In the simulations, pedestrians (blue disks) walk from their initial positions inside the blue rectangle to the intermediate target (yellow rectangle) at the beginning of the corridor and then to the final target (yellow square top of image). The queue measure in the second row (a.2-d.2) quantifies the shape of the crowd in front of the bottleneck. A queue measure of 0 would indicate that pedestrians queue in a single line in the middle of the corridor. Individual data points from 10 replicate simulation runs (a.2-

c.2) and the single experimental run (d.2) are shown in green. The black line is a spline regression through the scatter plot. The peak of the queue measure towards the end of simulations is caused by insufficient pedestrian numbers to maintain long queues. The third row (a.3-c.3) shows the observed stepping behaviour of all agents averaged over the 10 replicate simulations . The three heuristics produce different shapes in front of the corridor, which can be seen in both the snapshots and the quantitative queue measure.

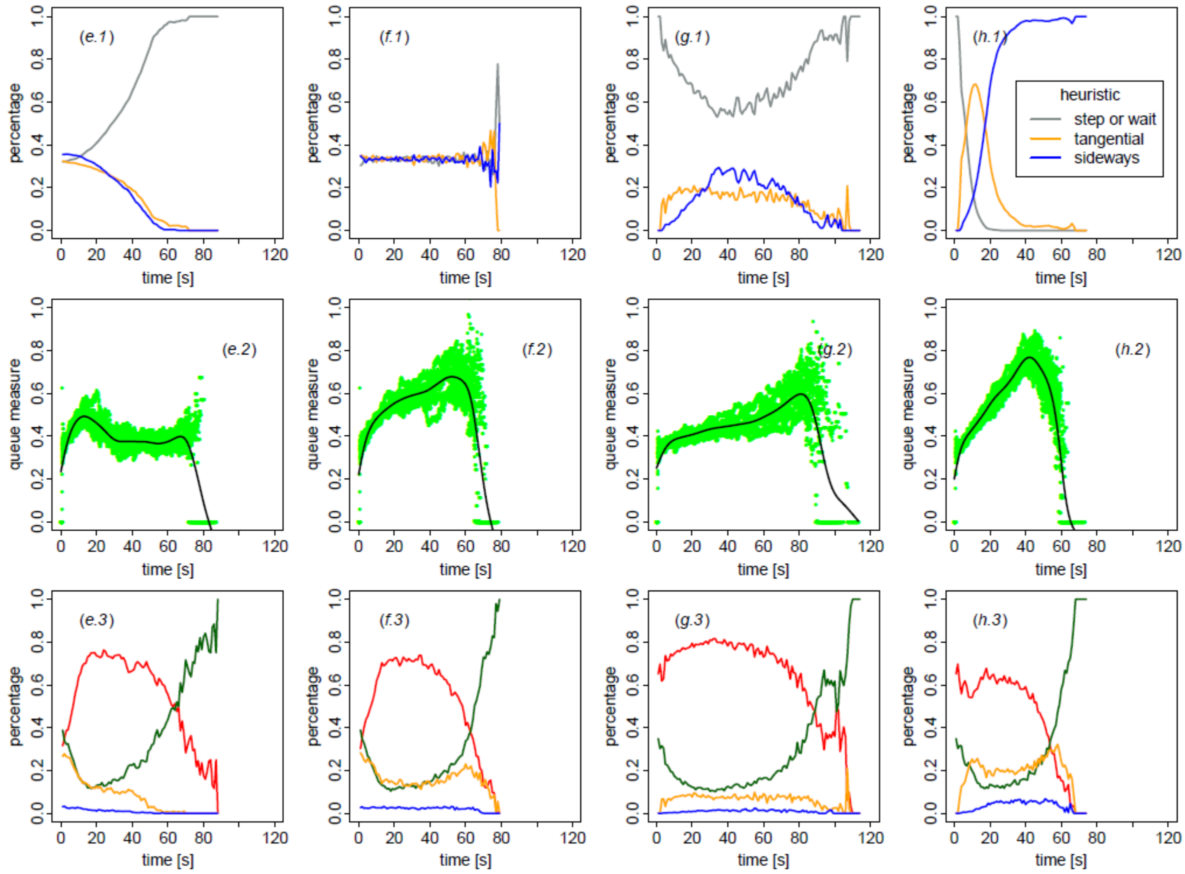

Figure 4: Analysis of the egress scenario (fig. 3) with combinations of the step or wait, tangential evasion, and sideways evasion heuristic. In e.1-3, individuals follow one of the heuristics with equal probability throughout the simulation run. In f.1-3, the probabilities are the same, but which heuristic they follow is newly decided for each step. In g.1-3, pedestrians follow the step or wait heuristic. After not moving for 3 steps, they follow the tangential evasion heuristic, and after 5 steps not having moved, they follow the sideways evasion heuristic. If they can move, they follow the step or wait heuristic again. In h.1-3, the same scheme is used, but pedestrians follow the heuristic for the rest of the run once they have chosen another one. The first row (e-h.1) shows which heuristics pedestrians

followed over time. The second row (e-h.2) reports the same queue measure used in fig. 3 and the last row (e-h.3) shows the observed stepping behaviour. The first row visualises the number of agents present in the simulation following the respective heuristics and supplements the interpretation of the emergent behaviour in the third row. We averaged the data of 10 simulation runs and 1 s in simulated time for the first and third row.

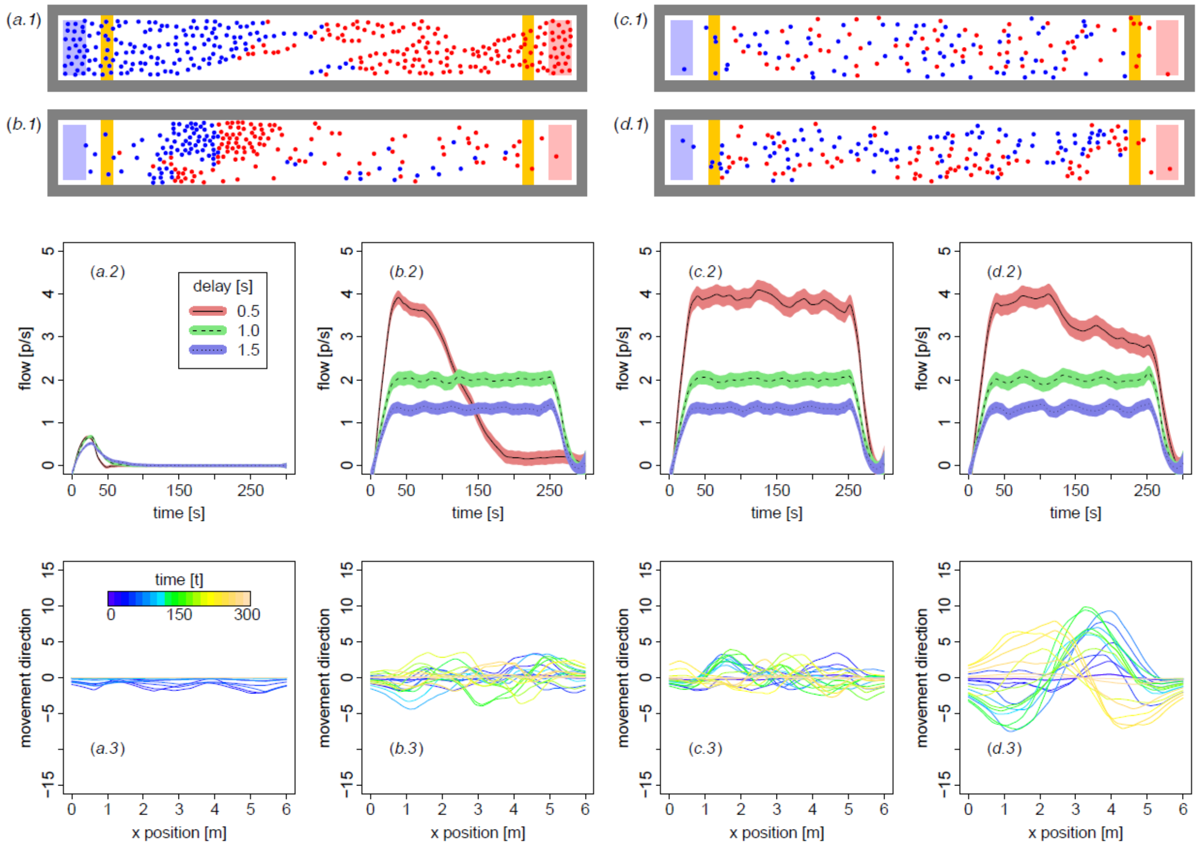

Figure 5: Results from corridor simulation study with the step or wait heuristic (a.1-3), tangential evasion heuristic (b.1-3), sideways evasion heuristic (c.1-3), and follower heuristic (d.1-3). We vary the rate at which pedestrians enter the corridor (lower delays between pedestrians imply higher rates). The snapshots are for simulations with a delay of 0.5 s and were taken 100 s after the start of the first simulation run (a.1-d.1). Blue circles depict pedestrians walking to the right and red circles pedestrians walking to the left. Pedestrians are created at the coloured rectangles (blue and red) at the ends of the corridor and walk to the opposite target (yellow rectangles). In the second row (a.2-d.2), the average flow of pedestrians in the middle of the corridor across 10 replicate simulations is shown with a 0.95 confidence interval of the regression line. The last row (a.3-d.3) shows our measure for lane formation

over the width of the corridor in the middle of the corridor in one simulation run with a delay of 1.0 s for one representative simulation run (supplementary table S8 for the average across simulation runs). The abscissa (x-axis) specifies the lateral position in the corridor. Positive values indicate more homogeneous flow in one direction, negative values more homogeneous flow in the other direction. Greater absolute values indicate a higher degree of lane formation. When following the step or wait heuristic, pedestrians cannot avoid each other and stop when they meet others walking in opposite direction. The tangential evasion heuristic and follower heuristic lead to occasional jams with at a delay of 0.5 s. The sideways evasion heuristic allows for flow without jams for all three delays. The follower heuristic produces the highest degree of lane formation.

Features Heuristic	Definition	Emergent behaviour in Bottleneck scenario	Emergent behaviour in Contra-Flow scenario	Potential cognitive effort (ordinal scale)	Cognitive demand
Step or wait heuristic	Pedestrians anticipate the next step but only take it if it does not lead to a collision.	Pedestrians do not overtake or walk around others, passive queueing.	Immediate congestion when pedestrians walking in opposite direction meet.	1	Anticipate step towards target, detect collisions
Tangential evasion heuristic	If the next step leads to a collision, pedestrians try to avoid it tangentially.	Pedestrians sometimes try to overtake and walk around others, no queueing.	Congestion with higher densities, minor lane formations	2 (contains step or wait heuristic)	+ determine tangential evasion directions, estimate distances
Sideways evasion heuristic	If tangential evasion fails, pedestrians then try to avoid the collision to the sides.	Pedestrians very frequently overtake and walk around others, no queueing.	Least likelihood of congestions, least lane formations	3 (contains tangential evasion heuristic)	+ determine sideways evasion directions
Follower heuristic	If a collision on the path towards the target is detected, pedestrians follow another individual walking in the same direction.	Similar to the chosen proximity evasion heuristic, active queueing if no proximity evasion is used.	Moderate likelihood of congestion with high densities, strongest lane formations	4 (contains sideways evasion heuristic)	+ determine walking directions of other pedestrians, select other pedestrian to follow

Table 1: Summary and comparison of different cognitive heuristics for pedestrians. The first column gives a brief definition of the heuristic. The second and third column describe emergent effects in the bottleneck and corridor simulation scenarios. The fourth column orders the heuristics on an ordinal scale according to how demanding they are in terms of cognitive effort. We only state that a heuristic with a higher value is at least as demanding as a heuristic with a lower value, but we do not attempt to quantify by how much heuristics differ in potential cognitive effort required. The last column summarises the cognitive demand each heuristic poses. More demanding heuristics include the cognitive demand from the heuristics above (indicated with a “+”).