Dynamic Motivation: Integrating Psychological Theories of Motivation in Pedestrian Modeling for Bottleneck Scenarios

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1 INTRODUCTION

Modeling pedestrian entrance scenarios is a central focus in the field of pedestrian dynamics, yet existing models, rooted in physics, have limitations when it comes to incorporating psychological aspects of individual behavior. Despite prior efforts to integrate certain psychological concepts, this interdisciplinary perspective is relatively new, and there is room for further exploration. This study aims to initiate a discourse on the integration of models of motivational changes into models for operational movement of pedestrians. Motivation is believed to be one of the most apparent psychological drivers of movement behavior in pedestrian environments, capable of significantly influencing crowd dynamics. For instance, congestion, a critical focus area in the field (Zanlungo *et al.*, 2023, Feliciani & Nishinari, 2018), arises from individual movement patterns and choices, reflecting the intrinsic motivation of the agents. While previous approaches have often employed a simplified binary categorization of motivation, classifying agents as either highly motivated or lowly motivated, this simplification, while useful in many contexts, fails to capture the complexity of motivation, which is influenced by a multitude of intrinsic and environmental factors. We introduce two critical dimensions of motivation: heterogeneity (variations in individual motivation levels within the crowd) and dynamism (fluctuations in motivation levels during goal pursuit) to establish a foundation for modeling motivation in entrance scenarios. The basis for these dimensions are based on experiments with pedestrians where the intensity of the forward movement was categorized using observation methods. The resulting data sets demonstrate both the dynamics and heterogeneity of the forward movement of the individual agents (Üsten *et al.*, 2022).

2 MOTIVATION

2.1 Motivation in Pedestrian Dynamics

Pedestrian experiments, particularly those incorporating bottleneck scenarios, have provided valuable insights into the effects of motivation. Researchers have investigated various corridor shapes, widths, and scenarios while manipulating participants' motivation levels using a high versus low dichotomy (Pastor *et al.*, 2015, Juliane *et al.*, 2020, Li *et al.*, 2021). Typically, motivation was primed through pre-instructions, where participants were asked to imagine scenarios artificially increasing their motivation (an exemplary instruction for high motivation being: 'Imagine you are on your way to a concert by your favorite artist.'). As expected, crowd dynamics such as density, flow, and acceleration exhibited different results between high and low motivation groups. Crowds instructed with high motivation tended to exhibit more active and assertive behavior, displaying a greater eagerness to reach the bottleneck quickly. Consequently, spatial and temporal crowd properties, such as density, exhibited greater increases in high motivation groups when compared to those receiving low motivation instructions.

In modeling, this dichotomous representation of motivation has also been used in certain scenarios (Xu *et al.*, 2021). Additionally, significant efforts have been made by Rzezonka *et al.* (2022) to define parameters assigned to agents that correspond to high and low motivation instructions. Two parameters, namely desired speed and time to get close to neighboring agents, were utilized to replicate the density outcomes observed in selected high and low motivation experiments through simulation. While high and low motivation instructions typically influence more factors than just speed and gap closing in real-life experiments (e.g., attention, shoulder/arm position, social interactions) (Üsten *et al.*, 2022), in simpler terms, these parameters were successful in reproducing the density results within a computer modeling environment. **The current study aims to introduce a model for these parameters to simulate motivational effects.**

2.2 Psychological Approach: Expectancy and Value

One approach to understanding motivation in contexts such as crowds is based on the expectancy and value concepts (Atkinson, 1964, Vroom, 1964), which posits that motivation is a function of an individual's expectations of success and the value they place on achieving the desired outcome. In the context of crowds, these expectations and values may be related to the individual's desire to exit the crowd safely and effectively. The expectancy and value definition of motivation could be well-suited to explaining motivation in bottleneck environments because it considers both the individual's expectations (the likelihood of reaching the bottleneck earlier) and the value they place on achieving their goals (the importance of reaching the bottleneck earlier). Moreover, this definition lends itself well to computer modeling, as both expectancy and value concepts can be numerically represented on a finite scale (ranging from no expectancy to maximal strength expectancy) (Vroom, 1964, Porter & Lawler, 1968).

Extending these concepts further, the expectancy concept refers to the degree to which a person believes a particular goal is probable (Vroom, 1964). In a bottleneck scenario, the initial perceived likelihood of success is primarily determined by an individual's initial position within the crowd. As individuals progress towards the exit, their perceived likelihood of success changes, fluctuating based on proximity to the exit and information about crowd movement (which we describe as 'competition'). Conversely, the value concept relates to the desirability or attractiveness of the potential outcome that can be achieved through individual behavior (Vroom, 1964, Porter & Lawler, 1968). In crowd scenarios, this typically involves quickly reaching the bottleneck, though the perceived value may vary with the context of the entrance process, as well as from pedestrian to pedestrian. In simulations, we can manipulate the value concept by assigning a function to agents' movement parameters, while this function depends on both the agent's properties and their real-time expectancy level.

3 MODEL

We build the motivation model on top of a simple operational velocity-based model Tordeux *et al.* (2016). The model is formally defined as

$$\dot{X}_i(X_i, X_j, \ldots) = \vec{e}_i(X_i, X_j, \ldots) \cdot V_i(X_i, X_j, \ldots), \tag{1}$$

where X_i is the position of agent i, V_i is a scalar denoting its speed, and $\vec{e}_i$ is a unit vector representing its direction of movement.

The direction of movement $\vec{e}_i$ is calculated first using the equation

$$\vec{e}_i = u \cdot \left(\vec{e}_i^{\,0} + \sum_{j \in J_i} k \cdot \exp\left(\frac{-s_{i,j}}{D}\right) \cdot \vec{n}_{i,j}\right). \tag{2}$$

Here, u is a normalization constant such that $\|\vec{e}_i\| = 1$. $\vec{e}_i^{\,0}$ is a unit vector representing the desired direction of the agent.

J_i is the set of agents that contains all neighbors affecting the moving direction of the agent i. The magnitude of the impact from these neighbors is a function of $s_{i,j}$, which is the distance between the edges of the agent i and j along the line connecting their centers. Parameters $k > 0$ and $D > 0$ are used to calibrate the strength and range of the impact, respectively. These parameters are directly related to the 'value' of each pedestrian. That means, pedestrians having a low value do not try to perform any aggress iv collision avoidance and stick to their desired target ($k \leq 1$).

Then the speed on the new moving direction is obtained using the equation

$$V_i = \min\left\{V_i^0, \max\{0, \frac{s_i}{T}\}\right\}. \tag{3}$$

The speed is a function of s_i, which is the maximum space of agent i in the new direction of movement $\vec{e}_i$ without overlapping with other agents.

In equation 3, V_i^0 is the free speed of the agent i, the speed that is achieved by moving without interference from other agents. The parameter $T > 0$ is the slope of the speed-headway relationship.

For our proposed motivation model we calculate the parameters V^0 and T depending on the value and expectancy of the agents, both being a continuous function of several factors, e.g., the distance to the exit and the density. See Figure 1.

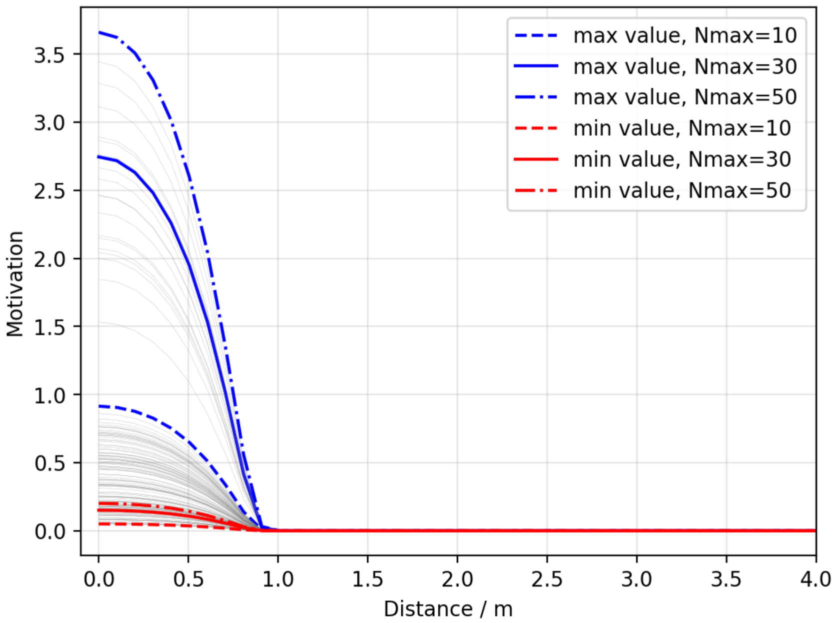

Figure 1 – *Screenshot of a simulation. We can observe that agents with lower 'value' fall back, while other agents with higher 'value' rush in the bottleneck.*

In Figure 2, we present a screenshot from a simulation illustrating our newly developed motivation model. It is evident from the simulation that agents exhibit diverse behaviors during evacuation from the bottleneck, which can be attributed to varying levels of motivation.

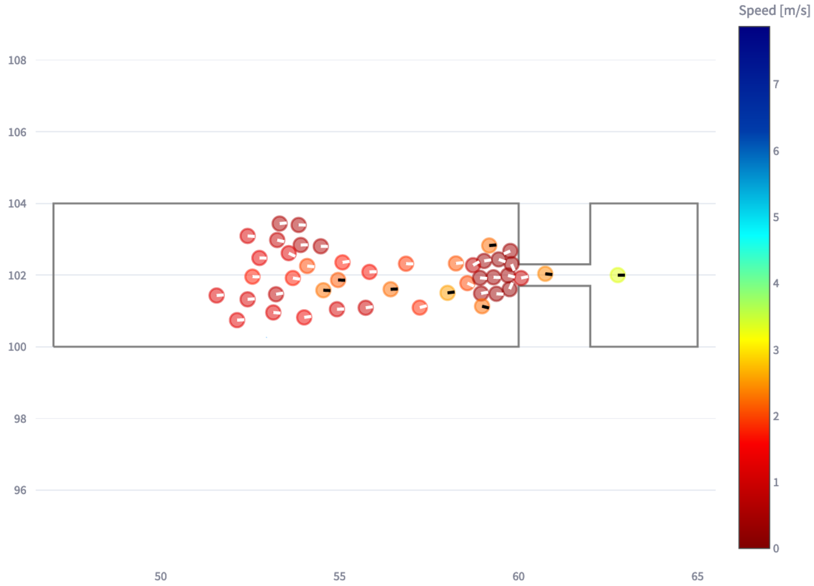

Figure 2 – *Screenshot of a simulation. We can observe that agents with lower 'value' fall back, while other agents with higher 'value' rush in the bottleneck.*

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