Single-file Movement: Literature Review, Empirical Analysis with Artificial Neural Networks, and Modeling

Dissertation to obtain a doctoral degree

in the
School of Mechanical Engineering and Safety Engineering

University of Wuppertal

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Wuppertal, 2025

Main Research Field: This thesis primarily contributes to Pedestrian Dynamics from a computer scientist's perspective.

Keywords: Single-file Movement, Single-file Motion, Single-File Flow, Pedestrian Dynamics, Fundamental Diagram, Experiment, Software, Microscopic Model, Least Squares Parameter Estimate, Stop-and-go Waves, Artificial Neural Networks, Distance Headway, Interaction Range, Modeling.

Dedication

This thesis is dedicated to my generous mother, Faize Subaih; my cherished teacher and father, Munjid Subaih (RIP); and my beloved siblings: Ala, Suhail, Diya, Hiba, Basim, and Basil. Last but certainly not least, to my supportive husband, Sameh Othman.

Abstract

Several influential factors impact pedestrian movement within crowds, making their analysis complex and challenging. To address this, we employ a simplified system referred to as single-file. In this system, pedestrians walk along a narrow path without overtaking, ensuring that the order of individuals remains constant. This setup reduces the number of variables and allows for a focused examination of the specific factors researchers aim to investigate in pedestrian dynamics. Given the significance of single-file movement in understanding complex movement behaviors, this thesis demonstrates the importance of studying single-file systems. Furthermore, this thesis analyzes the interaction ranges in single-file systems by incorporating into the speed model the influence of both the pedestrian ahead and the one behind, taking into account their respective distances and speeds. This novel approach, detailed in Publications II and III, enhances the accuracy of modeling in single-file movement.

This cumulative thesis comprises three publications aimed at investigating pedestrians' single-file movement. Publication I provides a comprehensive review of experiments on single-file pedestrian movement, emphasizing its importance. The review covers the historical background of single-file movement studies and offers insights from human and non-human traffic systems. The publication also elaborates on various experimental setups and data collection methods and discusses factors influencing pedestrian movement. Additionally, the study introduces a new Python-based tool, *SingleFileMovementAnalysis*, designed to analyze the data of pedestrian movement, particularly head trajectories, which helps prepare and calculate movement quantities such as speed, density, and headway. The publication offers an approach to experimental data analysis and suggests future directions for research in this field.

In Publication II, the factors influencing pedestrian movement in single-file experiments are explored. Feed-forward neural networks are utilized to predict individual pedestrians' speeds, using various combinations of distances and interaction ranges with neighboring pedestrians. Therefore, the influence of introducing the distance behind into the speed model is analyzed, and the predicted individual speeds using different influential factors are evaluated and compared.

Inspired by the results from the statistical investigations conducted in Publication II, Publication III introduces a new microscopic speed model that considers the relative distances to the nearest neighbors both behind and ahead for single-file movement. A fine-tuning of the weighted asymmetry parameters is applied, and the stability of the new model is analyzed. Furthermore, a numerical simulation of one-dimensional movement evaluates the proposed model.

Zusammenfassung

Mehrere Einflussfaktoren wirken sich auf die Bewegung von Fußgängern in Menschenmengen aus, was ihre Analyse komplex und schwierig macht. Um dieses Problem zu lösen, verwenden wir ein vereinfachtes System, das als Single-File bezeichnet wird. In diesem System gehen die Fußgänger auf einem schmalen Weg, ohne zu überholen, so dass die Reihenfolge der Personen konstant bleibt. Dieser Aufbau reduziert die Anzahl der Variablen und ermöglicht eine gezielte Untersuchung der spezifischen Faktoren, die die Forscher in der Fußgängerdynamik untersuchen wollen. Angesichts der Bedeutung der Bewegung in einer Reihe für das Verständnis komplexer Bewegungsabläufe zeigt diese Arbeit, wie wichtig die Untersuchung von Systemen in einer Reihe ist. Darüber hinaus werden in dieser Arbeit die Interaktionsbereiche in Ein-Fußgänger-Systemen analysiert, indem der Einfluss sowohl des vorausfahrenden als auch des nachfolgenden Fußgängers in das Geschwindigkeitsmodell einbezogen wird, wobei die jeweiligen Entfernungen und Geschwindigkeiten berücksichtigt werden. Dieser neuartige Ansatz, der in den Veröffentlichungen II und III detailliert beschrieben wird, erhöht die Genauigkeit der Modellierung bei einreihigen Bewegungen.

Die vorliegende kumulative Dissertation umfasst drei Publikationen, die sich mit der Untersuchung von Single-File-Bewegungen von Fußgängern befassen. Publikation I gibt einen umfassenden Überblick über Experimente zur Single-File-Bewegungen von Fußgängern und unterstreicht die Bedeutung dieses Forschungsgebiets. Der Bericht befasst sich mit dem historischen Hintergrund von Studien über Single-File-Bewegungen und bietet Einblicke in menschliche und nicht-menschliche Verkehrssysteme. Die Publikation geht auch auf verschiedene Versuchsaufbauten und Datenerhebungsmethoden ein und erörtert Faktoren, die die Fußgängerbewegungen beeinflussen. Die Studie stellt außerdem ein neues Python basiertes Tool, *SingleFileMovementAnalysis*, vor, welches für die Analyse von Fußgängerbewegungen, insbesondere deren Kopftrajektorien, entwickelt wurde. Es unterstützt außerdem die Berechnung von Bewegungsgrößen wie Geschwindigkeit, Dichte und Wegstrecke. Diese Publikation bietet einen Ansatz für die experimentelle Datenanalyse und schlägt zukünftige Forschungsrichtungen in diesem Bereich vor.

In der Publikation II werden die Faktoren untersucht, die die Bewegung von Fußgängern in Single-File-Experimenten beeinflussen. Feed-forward neuronale Netze werden zur Vorhersage der Geschwindigkeit einzelner Fußgänger eingesetzt, wobei verschiedene Kombinationen von Abständen und Interaktionsbereichen mit benachbarten Fußgängern verwendet werden. Der Einfluss auf das Geschwindigkeitsmodell durch die Einführung des Abstandes zum hinteren Nachbarn wird analysiert, und

die vorhergesagten individuellen Geschwindigkeiten werden unter Verwendung von verschiedenen Einflussfaktoren bewertet und verglichen.

Ausgehend von den Ergebnissen der statistischen Untersuchungen, die in der Publikation II durchgeführt wurden, führt die Publikation III ein neues mikroskopisches Geschwindigkeitsmodell ein, das die relativen Entfernungen zu den nächsten Nachbarn sowohl hinter als auch vor dem Fußgänger für die Single-File-Bewegungen berücksichtigt. Es wird eine Feinabstimmung der gewichteten Asymmetrieparameter vorgenommen, und die Stabilität des neuen Modells wird analysiert. Darüber hinaus wird das vorgeschlagene Modell durch eine numerische Simulation einer eindimensionalen Bewegung evaluiert.

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CHAPTER 1

Introduction

1.1 Background and Motivation

In events (sports, concerts) and daily commutes (shopping, going to work), people move alone, as a group, or in crowds in various environments (inside buildings, outside buildings). Many influential factors impact their movement, for example, pedestrian gender [1–3], social conventions [4], external motivations [5–8], etc., and phenomena can emerge such as stop-and-go waves [9–12], lane formation [13], etc. These parameters (variables and constants) are complex to analyze together to understand the impact of each in the movement, especially in the movement inside two-dimensional space.

The parameters controlling pedestrian movement should be investigated within a simple system to facilitate understanding the movement in complex situations. Seyfried et al. [14] introduced a single-file system in pedestrian dynamics that features pedestrians walking unidirectionally without overtaking, focusing on one-dimensional (1D) movement and limiting the potential effects that could influence the fundamental diagrams (FDs). This system is introduced to examine the relationship between density and flow or velocity referred to as the FD, which characterizes pedestrian movement. To date, approximately forty single-file pedestrian experiments have been conducted for various purposes (as reviewed in Publication I). These experiments mainly aimed to investigate the impact of various influential factors in the pedestrian dynamics [1, 2, 6–8] and movement characteristics [14–21]. In this context, a detailed understanding of the single-file movement is essential.

The significance of studying single-file motion lies in isolating the movement characteristics under investigation to describe relationships, such as the density-speed relationship. This type of system ignores the influence of pedestrian directional behavior (in 2D), focusing only on the longitudinal movement direction (in 1D). Although the single-file setup effectively isolates key factors influencing movement and enables the analysis of simple 1D motion, its applicability to real-world scenarios is limited. In real situations, movement is often multi-directional, and crowd behaviors are shaped by a more complex and broader range of factors. Therefore, single-file movement does not capture the behavior of pedestrians in multi-directional flows or the characteristics that emerge in complex crowd dynamics. In such scenarios, pedestrians are involved in interactions with obstacles or other groups, and the single-file system cannot account for behaviors like merging, overtaking, or avoidance tactics.

This cumulative thesis aims to develop a more in-depth understanding of single-file pedestrian movement through a combination of literature review, empirical analysis, and modeling. It provides a comprehensive review of single-file movement research, highlighting methodologies, influential factors, and trends in experimental design (Publication I). The thesis also introduces a novel approach to analyzing how the distances between pedestrians influence their speed, utilizing feed-forward neural networks (FFNN) to extract influential factors without modeling bias (Publication II). Finally, it introduces the modeling of anisotropic interactions in pedestrian dynamics by incorporating the distances with both preceding and following neighbors into a microscopic speed model, resulting in improved simulation of stop-and-go waves and enhanced accuracy in FDs (Publication III).

1.2 Single-file Movement

A single-file system in pedestrian dynamic as defined in the review (Publication I) is a group of interacting pedestrians walking in a narrow path (physical or virtual), where individuals are unable to pass each other (rule: no overtaking), and the order of the pedestrians remains constant throughout the experiment time. This system aims to examine the basic characteristics of pedestrian movement, including physical and psychological interactions, and to explore the fundamental relationship between density-flow and density-velocity (FD). The FD is used to quantify the capacity of pedestrian facilities, thereby enabling the assessment of escape routes, facilities capacities, and the evaluation of pedestrian models.

1.2.1 State of Research

This section briefly reviews the literature related to pedestrian single-file movement experiments and modeling. For a comprehensive review concerning the experimental research, the reader refers to Publication I. For studies about modeling, refer to the sections introduction and related work in Publications II and Publication III.

In the literature on pedestrian single-file, significant progress has been made in experimental research performed for various purposes. First, exploring movement quantities (speed, density, flow, etc.) or stepping behavior [14–21]. Second, to validate developed methods for extracting trajectories from video footage [22]. Third, to assess the effects of possible influential factors (e.g., age, gender, social conventions, motivation with music, etc.) on movement properties. Given the diversity of experimental research on single-file movement and its significance, a review article that defines and summarizes existing work on the topic is necessary.

Besides, the simplified system, characterized by unidirectional pedestrian flow with limited degrees of freedom, has provided critical insights into the relationships between density, speed, and headway. Previous studies have introduced several models in terms of the utilized modeling approach. Speed-based models refer to first-order differential equations where the speed of a pedestrian depends on the distances and velocities of the surrounding neighbors [9, 10, 23–26]. Some speed-based models include the time-to-collision parameter [27, 28]. Others include the stepping behavior parameters (i.e., step size, number of steps per unit time) [8, 19, 29]. Acceleration-based or force-based models are based on second-order differential equations which include external forces to derive the speed and position [12, 30–33]. Locomotion models simulate pedestrians by physical step rather than time step assuming that humans are bipedal creatures who move forward by stepping alternately with the left and right foot [34]. Cellular automaton, the discrete on-space models assume that pedestrian transit to a neighbor cell (unit of distance is cells) [35]. Most existing modeling approaches consider only the headway to the front, resulting in totally asymmetric interaction models. However, the distance with the pedestrian behind may also influence the behavior of a pedestrian. Moreover, some research areas remain open for further investigation, particularly in the application of data-driven approaches to predict speed without introducing modeling bias, such as through the use of artificial neural networks (ANNs).

This cumulative thesis contributes to these areas by addressing gaps through three publications. Publication I reviews single-file research across human and non-human systems, highlighting their methodologies, and influential factors investigated, highlighting the trends and the directions of future research in single-file experiments, and proposing the *SingleFileMovementAnalysis* tool for consistent data processing and analyzing movement quantities. Publication II introduces a novel modeling approach utilizing FFNNs to predict pedestrian speed. Publication III improves the microscopic speed model by introducing the distance with the pedestrian behind, providing enhanced stop-and-go waves and accuracy in one-dimensional pedestrian flow simulations. Together, these works establish a methodological framework for future single-file research, paving the way for new investigations.

1.2.2 Experimental Analysis and Modeling

Performing real single-file movement experiments involves actual environments, and conditions providing results that directly reflect real-world behaviors. These experiments lead to unexpected observations and emerging phenomena. However, the cost of performing experiments is higher than that of simulations, involving the costs of equipment, facilities, hiring people, etc. The availability of datasets and observations collected from experiments enables the reproduction of real pedestrian behavior using simulation. In computer simulation, the datasets collected from the experiments are used to calibrate the model's parameters and validate the model that describes pedestrian dynamics. Performing simulations is faster because it can quickly and easily repeat the same experiment several times. However, the simulation is biased by the modeler observing the real system and defining the model.

With the availability of datasets from previously executed real experiments, it can conduct literature, empirical, and modeling analyses to understand and predict pedestrian dynamics before effectively simulating movement in 1D. In this thesis, a new approach to exploring influential factors is proposed using single-file experimental data to predict and understand the individual speeds of pedestrians without introducing modeling bias. The novel approach of using ANNs to predict and understand single-file pedestrian motion without introducing modeling bias is an original contribution to the study. As explored in Publication II, the ANNs are used to approximate the relationship between the distances to pedestrians in front and behind, and the resulting pedestrian speed, which allows for a more accurate representation of real-world dynamics. Unlike traditional models, which typically assume an anisotropic interaction where the forward distance primarily governs speed, the ANN-based method captures the influence of the follower's headway as well. This isotropic interaction, where both front and behind distances are included, significantly enhances the accuracy of speed predictions. Including the follower's distance into the prediction model has shown improvements in speed estimation by up to 18% over traditional models. Finally, inspired by the results of Publication II, in Publication III mathematical modeling is used to describe the speed equation by introducing the distance behind the pedestrian, which was found to improve the predictions using the ANN.

1.2.3 Objectives and Methodology

The objective of this dissertation is to deepen the understanding of pedestrian single-file movement by integrating experimental literature analysis, data-driven approaches for empirical analysis (feature extraction), and mathematical modeling. This cumulative thesis systematically investigates the factors influencing pedestrian dynamics, with a specific emphasis on the anisotropy of interactions by considering not only the distance to the pedestrian ahead to model the speed but also to the follower. The thesis combines three interrelated contributions, each investigated in its respective publication, aligning to develop new methodologies and tools for extracting factors, analyzing, and modeling single-file pedestrian motion. Figure 1.1 illustrates the structure of the methodology used to achieve the thesis objectives.

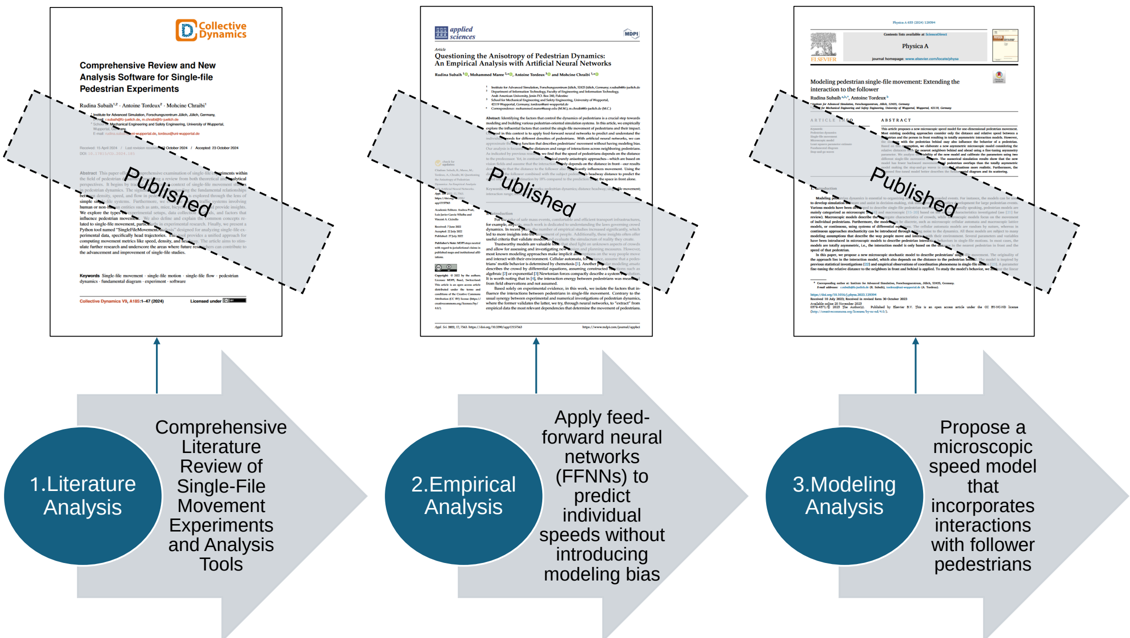

Figure 1.1: The methodology of the cumulative thesis and its published articles.

The first step in this thesis involves a comprehensive literature review, presented in Publication I, to establish the theoretical and experimental foundation for this thesis. The review systematically studies over 48 experimental studies focusing on single-file movement across human and non-human systems (ants, mice, bicycles, and cars). It identifies trends, methodologies, and gaps in single-file pedestrian dynamics while highlighting the significance of single-file systems in understanding fundamental relationships in pedestrian flow. As part of this contribution, a Python-based tool, *SingleFileMovementAnalysis*, is developed to standardize the analysis of single-file experimental data (the methodology is depicted in Figure 1.2).

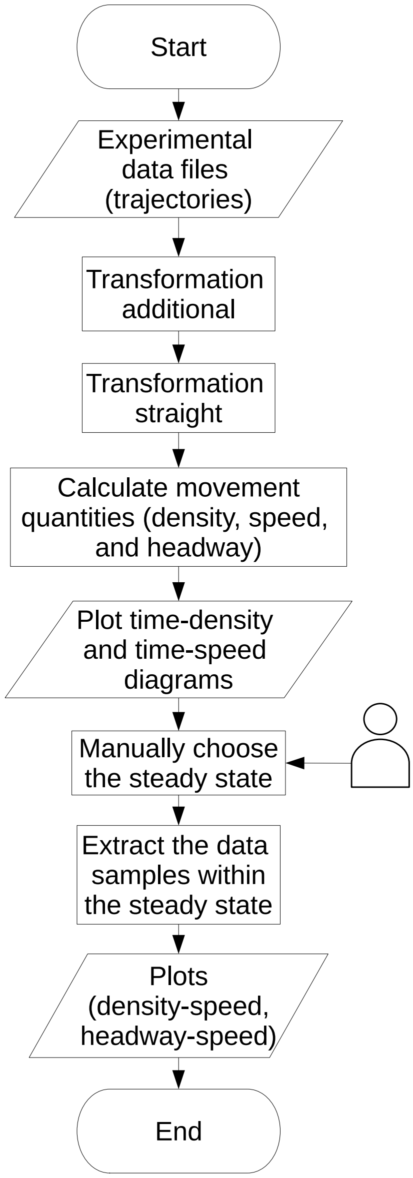

Figure 1.2: Flowchart for calculating movement quantities using head trajectories.

This tool automates the calculation of movement quantities such as speed and density, ensuring consistency in data processing and visualization, and providing a foundation for future analytical work. The metadata from ten experiments - including 28 publicly available datasets - have been collected and stored to ensure easy and rapid accessibility. This enables analysis replication and further research for this thesis and other researchers. The analysis tool tested over the 28 datasets comprises oval setup experiments producing the time-space, density-speed, and headway-speed diagrams. These one-dimensional datasets were collected from experiments conducted under varying conditions to investigate different aspects, including motivation-haste, stop-and-go waves, age, gender, etc. Head trajectories of pedestrians are available, enabling the calculation of the distances between the pedestrians and speeds over time. The resulting calculated movement quantities - density, headway, and speed- form a foundational dataset for subsequent data-driven and mathematical modeling in the following steps.

Building on the aforementioned empirical findings, Publication II focuses on a data-driven approach to predict pedestrian speed. The second step of the thesis is to apply FFNNs to predict the individual speeds of pedestrians walking in a single file. A novel approach to explore the influential factors and approximate the fitting function to describe pedestrians' movement without having modeling bias. Distances to both the predecessor and follower are used as input features, with the individual speed of pedestrians as the target output. We tried different FFNN structures with one and two hidden layers as follows: (1), (2), (3), (3, 2), (2, 2), (32, 32), and (64), where the expression (x) represent one network with an x number of hidden layers, and (x, y) represents two hidden layers, with a number x of hidden neurons in the first layer and a number y of neurons in the second hidden layer. The defined FFNNs are trained and tested using the experimental data, employing bootstrap resampling to minimize overfitting and using mean squared error as the loss function. As a result, the shallow FFNN with two hidden layers outperforms the other structures minimizing the MSE values (See Figure 1.3).

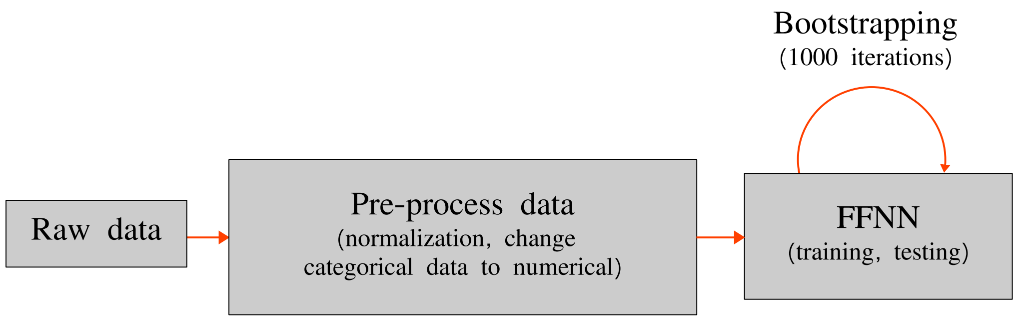

Figure 1.3: The methodology followed in developing the algorithms for speed prediction.

The third step of the thesis is inspired by the results of the empirical analysis in Publication III, where the new speed model incorporates the distance to the follower pedestrian. This microscopic speed model is developed to describe single-file pedestrian movement by incorporating interactions with both the predecessor and the follower pedestrians, capturing the anisotropic nature of pedestrian interactions (see Figure 1.4). Initially, models' parameters such as desired speed, time gap, pedestrian size, and asymmetry parameter (α) are calibrated using nonlinear least squares with two experimental datasets. Then, a linear stability analysis of the model is performed, determining a possible value of the asymmetry parameter in the model. Finally, numerical simulations are performed which indicate the model's

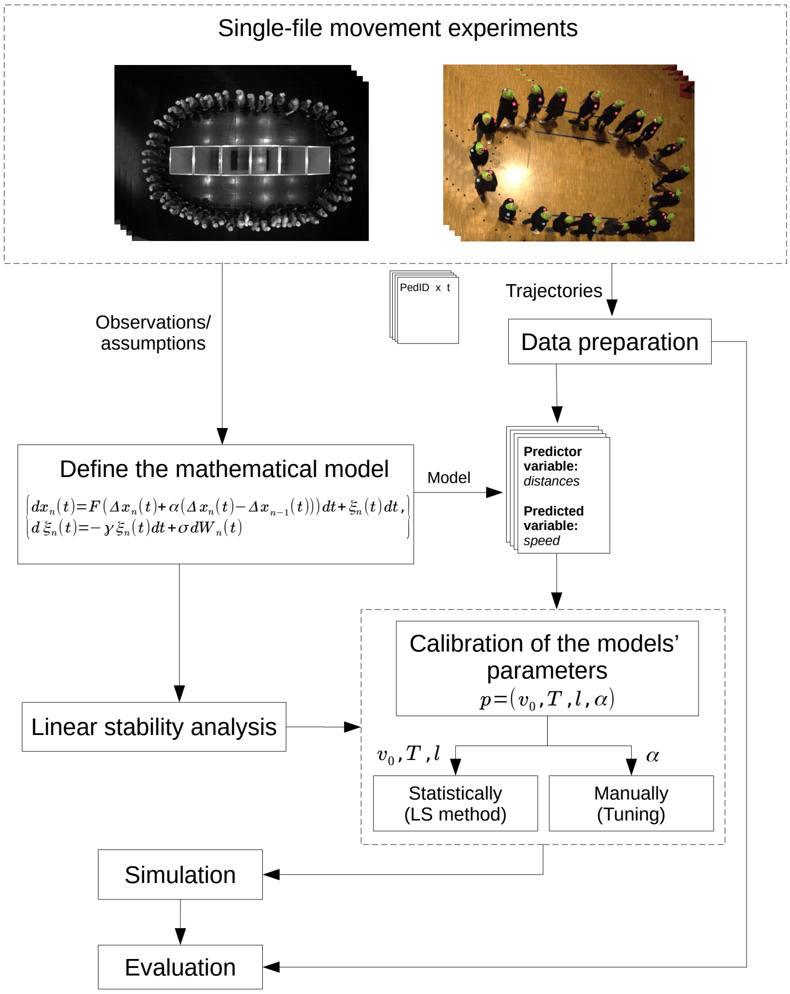

Figure 1.4: Key methodological milestones in the process of defining and evaluating the proposed pedestrian speed model.

capability to reduce unrealistic backward movements and pedestrian overlaps, resulting in more accurate stop-and-go wave patterns.

In the following chapters, Chapter 2 provides a concise overview of the three publications constituting this cumulative thesis. Subsequently, Chapter 3 discusses the obtained results, addresses the limitations of the conducted research, and proposes potential future investigations.

CHAPTER 2

Summary of Publications

This cumulative thesis consists of three publications: Publication I, Publication II, and Publication III. These publications are included at the end of the thesis. In this chapter, the research questions and results in the publications are summarized.

2.1 Publication I: Comprehensive Review and New Analysis Software for Single-file Pedestrian Experiments

This publication presents a thorough review of single-file experiments in pedestrian dynamics. This review begins with discussing historical perspectives and highlighting the significance of the single-file movement. It then compares the properties of human movement to those of non-human entities like ants and mice, providing insights into pedestrian dynamics. A generalized definition of the single-file movement system is introduced. The review also discusses the experimental setups, data collection methods, and the variables influencing pedestrian movement as investigated in the literature. The single-file system is important for establishing basic relationships that can contribute to more complex models and simulations in pedestrian dynamics, such as in crowd management. Additionally, this publication introduces a Python tool, *SingleFileMovementAnalysis*, designed to analyze data from these experiments, particularly focusing on pedestrian head trajectories. This software tool facilitates data analysis in single-file experimental research, enabling researchers to prepare, calculate, and analyze movement metrics (density, speed, headway) more efficiently. The paper is structured to guide future research by identifying gaps in current studies and suggesting directions for further exploration. It emphasizes the significance of single-file experiments in generating fundamental insights that are applicable across various pedestrian dynamic systems. Overall, the review serves as a comprehensive source of knowledge on single-file pedestrian experiments.

2.2 Publication II: Questioning the Anisotropy of Pedestrian Dynamics: An Empirical Analysis with Artificial Neural Networks

The publication explores the influential factors that impact the movement of pedestrians in single-file without modeling bias. Artificial neural networks are applied, namely FFNN to understand the effect of the combination of the distance ranges on the prediction of the pedestrian's speeds. The study aims to determine how distances to preceding and following neighbor pedestrians influence walking speed rather than the classical models that assume that the interactions mainly depend on the field of vision in front (anisotropic interactions). The research introduces a novel approach using FFNNs to empirically analyze pedestrian speed as a function of headway distances (the combination of the distance to the person directly in front and behind a pedestrian), without modeling biases. The empirical data for the study were collected through single-file experiments conducted at the Arab American University in Palestine [2] including homogeneous and heterogeneous gender groups. The researchers used this data to train and test different structures of FFNNs with a combination of input features (distance ranges), focusing on their impact on predicting pedestrian speeds. The study found that including the distance between the subject pedestrian with the follower and the predecessor improves speed prediction Mean-square error (MSE) accuracy significantly by 18% in comparison to using only the frontal distance. This suggests that interactions in pedestrian dynamics are not strictly anisotropic as in classical models, but rather that distances to both preceding and following pedestrians are important. Moreover, the results indicate that the influence of the following pedestrian becomes more pronounced in mixed-gender experiments, suggesting potential variations in pedestrian dynamics based on gender composition. In conclusion, the introduction of isotropic interactions improves the prediction of pedestrian speed in a single-file experiment compared to the anisotropic classical models. This insight could have significant implications for developing more accurate pedestrian dynamic models (similar to real behavior).

2.3 Publication III: Modeling pedestrian single-file movement: Extending the interaction to the follower

This publication proposes a microscopic speed model for pedestrian dynamics in one-dimensional movement. Unlike classical models, which only consider the distance and relative speed to the pedestrian directly in front, this new model introduces the interaction with the pedestrian behind, aiming to capture realistic interaction dynamics. The motivation behind this approach is the statistical investigations in Publication II and empirical observations of coordination phenomena in single-file motion [36]. The model development begins with the conceptualization of pedestrian interactions, followed by a mathematical formulation using the Optimal Velocity (OV) model [37], which involves stochastic differential equations to account for the randomness observed in pedestrian movement. This model adjusts interaction dynamics by fine-tuning the weight parameter (the model calibration) through a least squares method, which minimizes the difference between the observed and predicted pedestrian speeds. The calibration aims to balance the influences from the pedestrian ahead and the one behind. Two datasets from single-file experiments were used for the calibration [1, 2]. Furthermore, the theoretical analysis delves into the model's stability. It indicates conditions under which the model remains realistic and robust. Numerical simulation results show the model's effectiveness in replicating realistic pedestrian dynamics. The new model shows fewer backward movements and pedestrian overlaps than the totally asymmetric model (classical OV model) making the stop-and-go waves in crowded situations more realistic. Moreover, the proposed fine-tuned model better describes the FD (density-speed) and its scattering. Overall, this paper makes a significant contribution to the field of pedestrian dynamics by introducing pedestrian interactions and extending such models to more complex scenarios.

CHAPTER 3

Discussion and Outlook

This cumulative thesis contains a comprehensive literature review, empirical analysis, and mathematical modeling, to deepen the understanding of single-file dynamics. The findings obtained from studying the existing literature in Publication I, employing data-driven methods (Publication II), and improving the mathematical speed model by incorporating anisotropic interactions (Publication III), reveal both the potential and the limitations of focusing on single-file systems in pedestrian dynamics. In this section, we will discuss the thesis's key results and limitations, and then explore potential future directions.

The first manuscript [38] consolidates the existing body of experimental research in single-file motion and introduces a software tool that supports data preprocessing and analysis. The second manuscript [39] expands this foundation by applying FFNNs to explore whether pedestrians' speed depends not only on the distance to the predecessor but also on the distance to the follower, offering a novel perspective on isotropic interactions. Finally, the third manuscript [40], inspired by the aforementioned insights, develops a new mathematical model that incorporates the distance behind the pedestrian to describe the speed.

The review (in Publication I) defines and highlights the importance of single-file experiments as a simpler setting for understanding specific influential factors, movement characteristics, and phenomena. It covered various experimental setups, data collection methods, and the movement quantities commonly analyzed in such studies. By comparing human single-file movement with that of non-human entities like ants, mice, or bicycles, we found both similarities and differences that can inspire new approaches for modeling and improving pedestrian flow. The *Single-FileMovementAnalysis* software aims to standardize and simplify data processing and visualization. It provides a way for researchers to analyze head trajectories and compute movement metrics, ensuring that results are consistent and comparable. However, some limitations and open questions remain. For example, the cognitive and psychological aspects of how pedestrians perceive and react to their surroundings in a single-file are not fully understood. More research is needed in this direction. Also, the method of identifying steady-state conditions and defining them automatically is still an open issue. Moreover, integrating more advanced techniques or sensor data can offer deeper insights into the factors influencing the movement of pedestrians. Furthermore, the analysis tool introduced here can be expanded to include more geometric configurations and different types of trajectory data. By addressing these points, researchers can move closer to a more complete understanding of pedestrian behavior in single-file movement and how it relates to more complex crowd scenarios.

One of the remarkable results of our research is that incorporating both preceding and following neighbors improves the prediction of the individual speed, questioning the assumption that the distance to the pedestrian ahead alone governs movement. The empirical analysis using FFNNs suggests that pedestrians might respond, at least indirectly, to closeness from behind. However, the underlying explanation and causes remain uncertain. Integrating other types of data-driven methods and advanced statistical approaches could help explain the causes.

Furthermore, by incorporating the interaction with the follower into the optimal velocity model (in Publication III), we aimed to achieve a more realistic representation of pedestrian dynamics, particularly in high-density conditions. Compared to the classical, totally asymmetric approach, the proposed model shows in the simulation reduction in the backward movements, decreases the overlaps, and better reproduces the FD and its scattering. As a result, the simulated stop-and-go waves appear more realistic and closer to what is observed in real experiments. However, some aspects remain open for further investigation. Understanding the underlying reasons behind the influence of the interaction with the follower is still needed. For example, does this effect result from direct perception through vision or other senses, or does it emerge from more complex behavioral mechanisms? Future studies could include controlled experiments to verify how pedestrians perceive and react to their neighbors behind.

From the perspective of future research, several promising directions emerge. Experimentally, deeper analyses of pedestrians' perception and cognition could develop an understanding of pedestrian movement. Furthermore, the *SingleFileMovement-Analysis* tool [38], established in the first manuscript, can be readily extended and adapted to handle new geometries, data formats, or richer trajectory information (e.g., footstep-level data or three-dimensional body measurements). On the modeling side, experimental and empirical analysis should be performed to understand the possible causes of the isotropic interaction. Besides, additional evaluation in terms of validation and verification to assess the model's overall performance should be in future work. Also, the proposed asymmetric microscopic model should be benchmarked against various models found in the literature.

In conclusion, while single-file systems appear to reduce pedestrian movement to its most basic form, this research demonstrates that even these simple arrangements contain a wealth of hidden complexity. Such progress will not only deepen the theoretical understanding of how people move in single-file but will also open the door to broader, more meaningful applications. As these insights transition from theoretical models to practical strategies, they can improve how we understand, manage, and design crowded environments in the real world.

Bibliography

[1] Sarah Paetzke, Maik Boltes, and Armin Seyfried. "Influence of Gender Composition in Pedestrian Single-File Experiments". In: *Applied Sciences* 13.9 (2023), p. 5450.

[2] Rudina Subaih, Mohammed Maree, Mohcine Chraibi, Sami Awad, and Tareq Zanoon. "Experimental investigation on the alleged gender-differences in pedestrian dynamics: A study reveals no gender differences in pedestrian movement behavior". In: *IEEE access* 8 (2020), pp. 33748–33757.

[3] Rudina Subaih, Mohammed Maree, Mohcine Chraibi, Sami Awad, and Tareq Zanoon. "Gender-based insights into the fundamental diagram of pedestrian dynamics". In: *Computational Collective Intelligence: 11th International Conference, ICCCI 2019, Hendaye, France, September 4–6, 2019, Proceedings, Part I 11*. Springer. 2019, pp. 613–624.

[4] Ujjal Chattaraj, Armin Seyfried, and Partha Chakroborty. "Comparison of pedestrian fundamental diagram across cultures". In: *Advances in complex systems* 12.03 (2009), pp. 393–405.

[5] Guang Zeng, Andreas Schadschneider, Jun Zhang, Shibo Wei, Weiguo Song, and Rui Ba. "Experimental study on the effect of background music on pedestrian movement at high density". In: *Physics Letters A* 383.10 (2019), pp. 1011–1018.

[6] Cécile Appert-Rolland, Julien Pettré, Anne-Hélène Olivier, William Warren, Aymeric Duigou-Majumdar, Etienne Pinsard, and Alexandre Nicolas. "Experimental study of collective pedestrian dynamics". In: *arXiv preprint arXiv:1809.06817* (2018).

[7] Shigeyuki Ikeda, Takayuki Nozawa, Ryoichi Yokoyama, Atsuko Miyazaki, Yukako Sasaki, Kohei Sakaki, and Ryuta Kawashima. "Steady beat sound facilitates both coordinated group walking and inter-subject neural synchrony". In: *Frontiers in human neuroscience* 11 (2017), p. 147.

[8] Daichi Yanagisawa, Akiyasu Tomoeda, and Katsuhiro Nishinari. "Improvement of pedestrian flow by slow rhythm". In: *Physical Review E* 85.1 (2012), p. 016111.

[9] Antoine Tordeux and Andreas Schadschneider. "White and relaxed noises in optimal velocity models for pedestrian flow with stop-and-go waves". In: *Journal of Physics A: Mathematical and Theoretical* 49.18 (2016), p. 185101.

[10] Hua Kuang, Yanhong Fan, Xingli Li, and Lingjiang Kong. “Asymmetric effect and stop-and-go waves on single-file pedestrian dynamics”. In: *Procedia engineering* 31 (2012), pp. 1060–1065.

[11] Andrea Portz and Armin Seyfried. “Analyzing stop-and-go waves by experiment and modeling”. In: *Pedestrian and Evacuation Dynamics*. Springer, 2011, pp. 577–586.

[12] Andrea Portz and Armin Seyfried. “Modeling stop-and-go waves in pedestrian dynamics”. In: *Parallel Processing and Applied Mathematics: 8th International Conference, PPAM 2009, Wroclaw, Poland, September 13-16, 2009, Revised Selected Papers, Part II 8*. Springer. 2010, pp. 561–568.

[13] Andreas Schadschneider, Wolfram Klingsch, Hubert Klüpfel, Tobias Kretz, Christian Rogsch, and Armin Seyfried. “Evacuation dynamics: Empirical results, modeling and applications”. In: *arXiv preprint arXiv:0802.1620* (2008).

[14] Armin Seyfried, Bernhard Steffen, Wolfram Klingsch, and Maik Boltes. “The fundamental diagram of pedestrian movement revisited”. In: *Journal of Statistical Mechanics: Theory and Experiment* 2005.10 (2005), P10002.

[15] Yi Ma, Eric Wai Ming Lee, Meng Shi, and Richard Kwok Kit Yuen. “Spontaneous synchronization of motion in pedestrian crowds of different densities”. In: *Nature human behaviour* 5.4 (2021), pp. 447–457.

[16] Cheng-Jie Jin, Rui Jiang, and Da-Wei Li. “Influence of bottleneck on single-file pedestrian flow: Findings from two experiments”. In: *Chinese Physics B* 29.8 (2020), p. 088902.

[17] Cheng-Jie Jin, Rui Jiang, Ruiwen Li, and Dawei Li. “Single-file pedestrian flow experiments under high-density conditions”. In: *Physica A: Statistical Mechanics and its Applications* 531 (2019), p. 121718.

[18] Yi Ma, Ying Ying Sun, Eric Wai Ming Lee, and Richard Kowk Kit Yuen. “Pedestrian stepping dynamics in single-file movement”. In: *Physical Review E* 98.6 (2018), p. 062311.

[19] Weiguo Song, Wei Lv, and Zhiming Fang. “Experiment and modeling of microscopic movement characteristic of pedestrians”. In: *Procedia Engineering* 62 (2013), pp. 56–70.

[20] Asja Jelić, Cécile Appert-Rolland, Samuel Lemercier, and Julien Pettré. “Properties of pedestrians walking in line: Fundamental diagrams”. In: *Physical review E* 85.3 (2012), p. 036111.

[21] Asja Jelić, Cécile Appert-Rolland, Samuel Lemercier, and Julien Pettré. “Properties of pedestrians walking in line. II. Stepping behavior”. In: *Physical Review E* 86.4 (2012), p. 046111.

[22] Xuan Liu, Weiguo Song, and Jun Zhang. “Extraction and quantitative analysis of microscopic evacuation characteristics based on digital image processing”. In: *Physica A: Statistical Mechanics and its Applications* 388.13 (2009), pp. 2717–2726.

[23] Martin Friesen, Hanno Gottschalk, Barbara Rüdiger, and Antoine Tordeux. "Spontaneous wave formation in stochastic self-driven particle systems". In: *SIAM Journal on Applied Mathematics* 81.3 (2021), pp. 853–870.

[24] Andreas Schadschneider and Antoine Tordeux. "Noise-induced stop-and-go dynamics in pedestrian single-file motion". In: *Collective Dynamics* 5 (2020), pp. 356–363.

[25] Christian Eilhardt and Andreas Schadschneider. "Stochastic headway dependent velocity model for 1d pedestrian dynamics at high densities". In: *Transportation Research Procedia* 2 (2014), pp. 400–405.

[26] Antoine Tordeux, Mohcine Chraibi, and Armin Seyfried. "Collision-free speed model for pedestrian dynamics". In: *Traffic and Granular Flow'15*. Springer. 2016, pp. 225–232.

[27] Jakob Cordes, Mohcine Chraibi, Antoine Tordeux, and Andreas Schadschneider. "Time-to-collision models for single-file pedestrian motion". In: *Collective Dynamics* 6 (2021), pp. 1–10.

[28] Ioannis Karamouzas, Brian Skinner, and Stephen J Guy. "Universal power law governing pedestrian interactions". In: *Physical review letters* 113.23 (2014), p. 238701.

[29] Zhi-Ming Fang, Wei-Guo Song, Xuan Liu, Wei Lv, Jian Ma, and Xia Xiao. "A continuous distance model (CDM) for the single-file pedestrian movement considering step frequency and length". In: *Physica A: Statistical Mechanics and its Applications* 391.1-2 (2012), pp. 307–316.

[30] Antoine Tordeux, Mohcine Chraibi, Andreas Schadschneider, and Armin Seyfried. "Influence of the number of predecessors in interaction within acceleration-based flow models". In: *Journal of Physics A: Mathematical and Theoretical* 50.34 (2017), p. 345102.

[31] Mohcine Chraibi. "Oscillating behavior within the social force model". In: *arXiv preprint arXiv:1412.1133* (2014).

[32] Armin Seyfried, Bernhard Steffen, and Thomas Lippert. "Basics of modelling the pedestrian flow". In: *Physica A: Statistical Mechanics and its Applications* 368.1 (2006), pp. 232–238.

[33] Armin Seyfried, Andrea Portz, and Andreas Schadschneider. "Phase coexistence in congested states of pedestrian dynamics". In: *Cellular Automata: 9th International Conference on Cellular Automata for Research and Industry, ACRI 2010, Ascoli Piceno, Italy, September 21-24, 2010. Proceedings 9*. Springer. 2010, pp. 496–505.

[34] Zhongyi Huang, Mohcine Chraibi, and Weiguo Song. "Simulation of pedestrian single-lane movement by a biped model". In: *Physical Review E* 98.4 (2018), p. 042309.

[35] Ujjal Chattaraj, Armin Seyfried, Partha Chakroborty, and Manoj Kumar Biswal. "Modelling single file pedestrian motion across cultures". In: *Procedia-Social and Behavioral Sciences* 104 (2013), pp. 698–707.

[36] Kevin W Rio, Christopher K Rhea, and William H Warren. "Follow the leader: Visual control of speed in pedestrian following". In: *Journal of vision* 14.2 (2014), pp. 4–4.

[37] Antoine Tordeux and Armin Seyfried. "Collision-free nonuniform dynamics within continuous optimal velocity models". In: *Physical Review E* 90.4 (2014), p. 042812.

[38] Rudina Subaih, Antoine Tordeux, and Mohcine Chraibi. "Comprehensive Review and New Analysis Software for Single-file Pedestrian Experiments". In: *Collective Dynamics* 9 (Oct. 2024), pp. 1–47. ISSN: 2366-8539. DOI: 10.17815/cd.2024.185. URL: http://dx.doi.org/10.17815/CD.2024.185.

[39] Rudina Subaih, Mohammed Maree, Antoine Tordeux, and Mohcine Chraibi. "Questioning the Anisotropy of Pedestrian Dynamics: An Empirical Analysis with Artificial Neural Networks". In: *Applied Sciences* 12.15 (July 2022), p. 7563. DOI: 10.3390/app12157563.

[40] Rudina Subaih and Antoine Tordeux. "Modeling pedestrian single-file movement: Extending the interaction to the follower". In: *Physica A: Statistical Mechanics and its Applications* 633 (Jan. 2024), p. 129394. DOI: 10.1016/j.physa.2023.129394.

PUBLICATION I

Comprehensive Review and New Analysis Software for Single-file Pedestrian Experiments

This article has been published by Subaih, R., Tordeux, A., and Chraibi, M. (2024). Comprehensive Review and New Analysis Software for Single-file Pedestrian Experiments. Collective Dynamics, 9, 1–47.
DOI: https://doi.org/10.17815/CD.2024.185.

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Comprehensive Review and New Analysis Software for Single-file Pedestrian Experiments

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Abstract

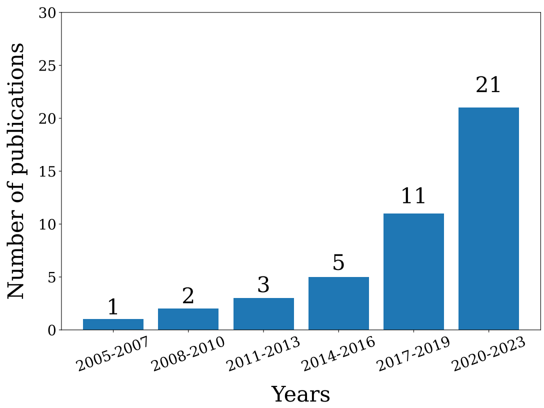
This paper offers a comprehensive examination of single-file experiments within the field of pedestrian dynamics, providing a review from both theoretical and analytical perspectives. It begins by tracing the historical context of single-file movement studies in pedestrian dynamics. The significance of understanding the fundamental relationships between density, speed, and flow in pedestrian dynamics is explored through the lens of simple single-file systems. Furthermore, we examine various traffic systems involving human or non-human entities such as ants, mice, bicycles, and cars, and provide insights. We explore the types of experimental setups, data collection methods, and factors that influence pedestrian movement. We also define and explain the common concepts related to single-file movement, particularly in experimental research. Finally, we present a Python tool named "SingleFileMovementAnalysis" designed for analyzing single-file experimental data, specifically head trajectories. This tool provides a unified approach for computing movement metrics like speed, density, and headway. The article aims to stimulate further research and underscore the areas where future researchers can contribute to the advancement and improvement of single-file studies.

Keywords: Single-file Movement, Single-file Motion, Single-File Flow, Pedestrian Dynamics, Fundamental Diagram, Experiment, Software

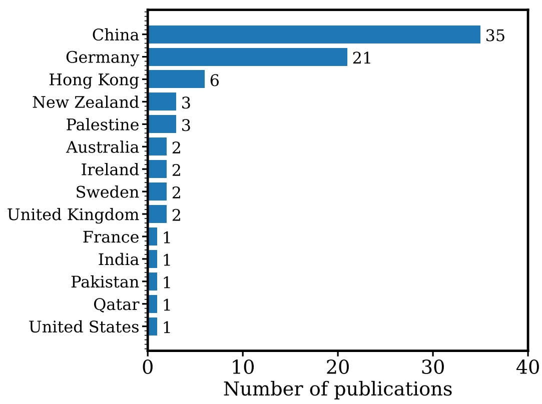
1 Introduction

In their seminal work, Seyfried et al. [1] present the concept of single-file movement in pedestrian dynamics to explore the relationship between density, flow, and mean velocity, also known as the fundamental diagrams, within pedestrian traffic. The fundamental diagram quantifies the capacity of pedestrian facilities, allowing the assessment of escape routes and the evaluation of pedestrian models. To assess dependence on the fundamental diagram, Seyfried et al. investigate experiments of single-file movement, where pedestrians walk unidirectionally along a line with reduced degrees of freedom. This restricts the possible factors that influence the fundamental diagram. In 2009, Chattaraj et al. [2] replicated the same experiment in India [1], with the main aim of analyzing the cultural influence (social conventions) on pedestrians' movement. The motivation behind performing single-file experiments, as pointed out by Chattaraj et al., is that the density-speed relation is influenced by multiple factors that are still not completely understood. In general, the importance of studying single-file movement can be traced back to the open questions: Which factors influence the fundamental relationships? What are the possible movement quantities that describe the walking characteristics of pedestrians?

Over the past decade, several experiments have been conducted to explore single-file movement. The objective of these experiments is to identify basic relationships within a system using a minimal number of variables and parameters. In these experiments, researchers typically set up a controlled environment in which pedestrians are asked to walk through a narrow corridor without overtaking. Figures I.1(a) and I.1(b) show the publication trends over the years and countries/territories, respectively. The surge in publications in recent years shows a rising interest in single-file



(a) Publications by year.



(b) Publications by country/territory (based on the affiliation of the authors).

Figure 1: The number of publications that mentions *single-file movement pedestrian dynamics* or *single-file motion pedestrian dynamics*, according to a Scopus search on 29 March 2024.

movement in pedestrian dynamics. However, it is worth noting that the terminology *single-file movement pedestrian dynamics* or *single-file motion pedestrian dynamics* is a relatively recent concept that, until now, has not been well-established (see the number of publications in Figure I.1(a)). We can divide the research focus of publications on single-file movement in pedestrian dynamics into four main topics: experiments, data analysis, modeling, and experiments with models (see Figure 2).

Given the importance of single-file experimental research, conducting a comprehensive literature review is essential to identify the gaps in previous studies and outline directions for future research. Xue et al. [3] examine and compare pedestrian single-file experiments from a modeling perspective. They compare the basic characteristics of pedestrian movement in the literature. Their work covers methods for measurement, data extraction, stepping behavior quantities, influential factors, and simulations of single-file pedestrian flow. Still, a more in-depth review, focusing on the details of the experiments from a data analytical viewpoint, is required. In this work, we explore various traffic systems, including humans, mice, ants, bicycles, and cars, to identify similarities and differences that can improve pedestrian dynamics. Furthermore, we define different pedestrian single-file systems and discuss their types. We characterize the types of experimental setups and identify factors that influence movement, along with discussion. Moreover, we propose a methodology for preparing trajectory data and calculating movement quantities using an open-source Python tool called "SingleFileMovementAnalysis" [4], which is essential for enabling future research to build on.

The subsequent sections of this paper are structured as follows. In Section 2, we explore the single-file traffic systems available in the literature and provide comparative insights. Additionally, we characterize single-file pedestrian systems. In Section 3, we review the single-file experiments in the literature focusing on the type of setups. In Sections 4, we explore the data collection methods adopted and the movement quantities investigated in the single-file experimental research. In Section 6, the factors influencing pedestrian movement are identified and studied. In Section 7, we propose a methodology for preparing trajectory data, computing in a systematic way movement quantities and present a Python software tool to analyze single-file movement data. Finally, in Sections 8 and 9, we provide a summary of the findings, identify trends and open issues, and suggest future research directions.

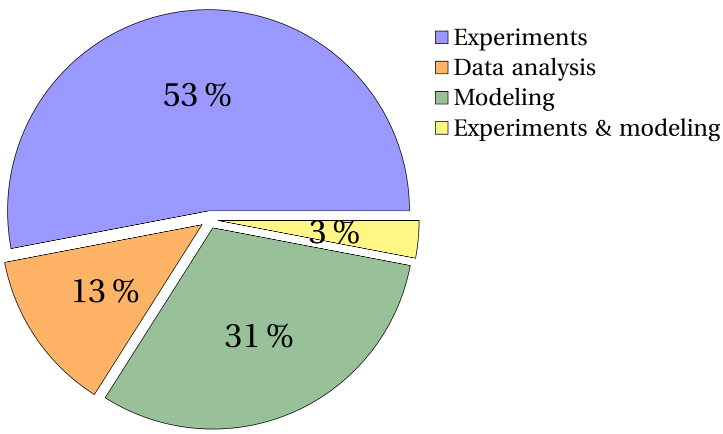


Figure 2: The percentage distribution of single-file movement publications in pedestrian dynamics across various subjects, from the literature reviewed for this paper.

2 Exploring Single-File Traffic Systems: Definition and Comparative Insights

Several single-file experiments have been conducted to investigate human movement [1, 2, 5–41]. After reviewing the literature above, we define the *single-file pedestrian system*, following the general definition of a system as described by Backlund et al. [42], as a group of interacting pedestrians walking in a narrow path (physical or virtual path [22]), where individuals cannot pass each other (rule: no overtaking). The order of the pedestrians remains constant throughout the experiment. In this context, the system aims to question the basic elements of pedestrian movement, including physical and psychological interactions.

The single-file system can be a *closed system* or an *open system*. In a closed system, pedestrian movement is influenced by elements within the system. Whereas in an open system, the surroundings can influence pedestrian movement. The term “surroundings” refers to the environment adjacent to the area of interest. For example, when pedestrians leave the predefined system boundaries and interact with the external environment. Further explanation of the open and closed single-file systems is described in Section 3. Having defined the pedestrian single-file system, this section aims to identify similarities between human and non-human single-file systems. We examine the basic principles of movement that govern these systems and identify possible movement similarities.

Exploring other single-file systems involving non-human entities offers valuable insights into understanding movement properties and relations in these systems. For example, studying the adaptive behaviors of ants and mice, and observing the movement of bicycles, and cars in response to movement stimuli (obstacles, other nearby entities, etc.) can inspire innovative modeling or crowd management approaches. Table 3 in Appendix A summarizes all single-file experiments reviewed in this article for various traffic systems.

Many non-human single-file systems, such as those observed in insects and rodents within animal societies, have been explored in the literature [43, 44]. Both systems (mice and ants) show that speed decreases with increasing density and exhibit a piecewise linear relationship between headway distance and speed, similar to the human system. However, scattered data points are observed in these relationships. The researchers attribute this primarily to random pauses. For example, Xiao et al. [43] find that at all densities, mice stop under various circumstances, including spontaneous pauses, space constraints, and tail effects (when a mouse stops or retreats after being touched by the tail of another). Similarly, Wang et al. [44] observe that ants exhibit random pauses during their experiments. Unlike in human systems, stopping occurs at high densities only when insufficient space is available to move forward [45].

Another difference is that mice and ants do not maintain personal space while walking, resulting in increased speed and flow at high densities. For instance, in the experiment with mice, the flow remains almost constant at high densities (non-dimensional density above 0.4) because the mice tend to make contact and move on top of each other, a behavior we refer to as overlapping. Like in experiments with ants, behaviors such as touching and moving backward are observed. Unlike the human system, where flow and speed decrease at high densities because pedestrians maintain some distance to avoid collisions and touching others. We recognize that differences in movement can be attributed to the dissimilar physical attributes (i.e., body size and shape), cognition, and decision-making processes of humans and non-human beings. However, we assume that touching and pausing behavior helps to gain insight into improving flow in high densities (short headway distances less than personal space).

Another group of single-file systems studied in the literature is vehicular systems. Research on vehicular single-file movement shows good agreement between studies regarding the relationship between certain movement quantities [46], such as the density-flow and density-speed. However, vehicles such as bicycles [14, 46, 47] and both human-driven and autonomous cars [48–51], are machines controlled by humans. This indicates that the movement of these vehicles is systematic and dominated by the physical constraints on the car, such as inertia and limitations on possible acceleration. We assume that investigating vehicular systems helps us understand how humans make decisions to control vehicles, addressing three main concerns: following instructions, avoiding collisions, and ensuring safety. Thus, the benefits of studying pedestrian dynamics from studying vehicular traffic can be linked to understanding cognitive processes. The differences and similarities in the motion properties among single-file traffic systems (such as pedestrians, mice, ants, bicycles, and cars) are summarized in Table 1.

Table 1: Comparison of movement characteristics among different single-file traffic systems.

Traffic system	**Keep distance in front**	**Sensitivity to distance in front in controlling the speed**	**Overlap behavior**	**Pauses/stopping behavior**	**Backward movement**
Human	Yes, respect personal space	Sensitive	Does not occur	Stop-and-go waves at high densities	Rarely (when someone unintentionally collides with the proceeding)
Mice	No	Not sensitive	Occurs	At all densities (spontaneous pauses because of space constraints, and tail effects)	-
Ants	No	Not sensitive	Occurs	Short pauses	Occurs (despite the large distance available in front)
Bicycles	Yes, keep distance to avoid potential collisions	Sensitive	Does not occur	Stop-and-go-waves at high densities	Does not occur
Cars	Yes, keep distance to avoid potential collisions	Sensitive	Does not occur	Stop-and-go-waves at high densities	Does not occur

3 Types of Experimental Setups

This section reviews the setup configurations and discusses their distinct features of single-file experiments involving pedestrians. We also present previously studied setup types in the literature and provide some insights.

Experimental studies on pedestrians' single-file movement have been performed in various shapes/types of setups (see Figure 3): oval [1, 2, 5, 6, 8, 11–13, 17, 19, 21, 25, 26, 28, 29, 32–34, 38, 39, 41], circle [7, 9, 10, 14, 16, 22, 24, 32], stairs [15, 35, 36], one-dimensional observation area [22, 27, 31], square with four straight corridors and four arcs [40], rectangle [30], rectangle with four straight corridors and four arcs [23], ship corridor [20], branch [37], seat aisle [18], flood [52].

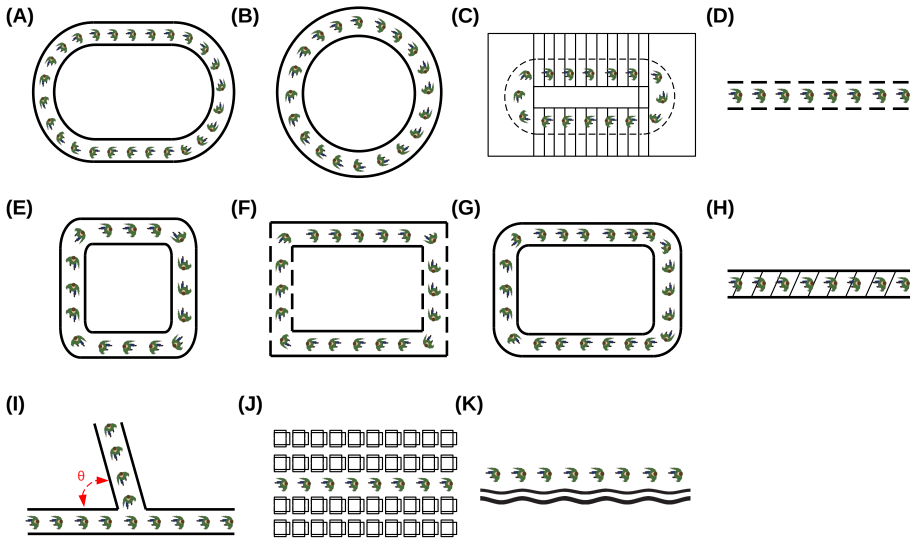


Figure 3: Illustrations of the experimental setups for different evacuation scenarios: (A) Oval (B) Circle (C) Stairs (D) One-dimensional observation area (E) Square with four straight corridors and four arcs (F) Rectangle (G) Rectangle with four straight corridors and four arcs (H) Ship corridor (I) Branch (J) Seat aisle (K) Flood.

We observe that the selection of the shape/type of the experimental setup is contingent upon the *evacuation scenario* the authors intend to investigate. After reviewing the literature, we categorize single-file experiments into five evacuation scenarios based on the evacuation facility under study: flood (moving in water), stairs, ships, seat aisles, and ground level (in general).

Here, we provide a brief overview of the relevant literature on the evacuation scenario in flood, stairs, ship corridors, and seat aisles. Li et al. [52] investigate the effectiveness of different formations for evacuating pedestrians during a flood. The authors perform experiments with a pool, using a single-file system at two specific water depths (0.35 m and 0.60 m), and compare the efficiency of evacuations with and without a rescue rope. The study finds that using a rescue rope in single-file formation during flood evacuations significantly reduces pedestrian fatigue and increases speed, particularly in higher water depths. In the investigation of stair evacuation, Chen et al. [15] conducted experiments exploring the movement characteristics of pedestrians ascending and descending stairways. The results show that descending stairs is faster than ascending, as pedestrians benefit from gravity during descent, whereas ascent requires more effort, resulting in slower speeds. Furthermore, the speed in stairways described by the number of steps in the longitudinal direction. Wang et al. [35] further investigate the impact of stair configuration and explore the influence of stair dimensions on pedestrian movement characteristics. The authors find that the stair configuration, particularly tread depth and riser height, significantly affects pedestrian movement speed, with steeper stairs leading to reduced walking speed. Ye et al. [36] compare pedestrian movement under motivation (fast walking) with normal walking. The results show that pedestrians on stairs move faster when motivated (fast walking condition), with descending movements being quicker than ascending ones, and that motivation increases velocity correlation between adjacent pedestrians.

Shifting the focus to evacuation in ship corridors, Sun et al. [20] design a simulator for ship corridors to explore the impact of trim (ship's tilt along its length) and heeling (ship's tilt to one side) on walking characteristics. The results indicate that the trim and heeling angles affect the pedestrian walking speed, with trim angles having a greater impact than heeling. Lastly, for seat aisle evacuations, Huang et al. [18] explore the effects of inactive pedestrians (non-moving), and aisle width's impact on pedestrian dynamics. They find that in narrow seat aisles, pedestrian walking speed increases as aisle width increases up to 0.40 m, after which it stabilizes, and that interactions with inactive pedestrians can significantly slow down the flow, particularly in narrower aisles. While the studies above offer valuable perspectives on single-file movement, our research aims to narrow the focus to ground-level experiments.

In ground-level experiments, various shapes/types of setups are explored. We divide them into two groups depending on the boundary conditions under which the experiment is conducted: *open* (open system) or *closed boundary conditions* (closed system). Experiments under open boundary conditions include setups with open entrances so pedestrians can enter and leave during the experiment. Examples include branch and one-dimensional observation areas. Lian et al. [37] employ a branch setup in which pedestrian streams from two entrances converge into a single main channel to reach the exit. The authors aim to explore pedestrian movement properties through single-file merging experiments, varying merging angles and inflow rates. In the one-dimensional observation area, Appert-Rolland et al. [22] conducted unidirectional experiments to investigate collective and individual decisions in walking. In other words, they study how pedestrians adapt their trajectories and velocities while walking freely in a group of people, rather than moving within a fixed density of pedestrians. During the experiments, pedestrians move along a fixed straight line across the facility, one after the other, following a leader who walks at either their free velocity or a prescribed low velocity.

Huang et al. [27] performed a one-dimensional observation area experiment to analyze the impact of luggage on pedestrian flow at traffic terminals. Participants are instructed to imitate walking in a terminal by following the queue while passing through the observation area. Wang et al. [31] also conduct a one-dimensional observation area experiment to study knee and hand crawling evacuations in fire accidents. Participants pass through a narrow channel divided into two parts: an upright walking area and a knee and crawling area, allowing the investigation of the sole movement characteristics of pedestrians and their movement properties under an increasing inflow at the channel's entrance. In the aforementioned studies, we observe that the authors opted for an open-boundary setup because they are interested in monitoring inflow and outflow as experimental setups.

In experiments under closed boundary conditions, the configuration is enclosed, enabling pedestrians to move within the setup without exiting during the experiment. Examples include an oval, circle, rectangle, a rectangle with four straight corridors and four arcs, and a square with four straight corridors and four arcs. The most commonly explored shape/type is the oval; approximately 52% oval from the total single-file experiments reviewed for this article (for all evacuation scenarios). Seyfried et al. [1] are the first researchers who introduce the oval setup for pedestrian's single-file experiments. The authors explain that the oval setup, similar to the one in [53], limits the number of test objects in the experimental setup and achieves high density without boundary effects. Besides, implementing circular guiding of the passageway gives periodic boundary conditions.

Experiments involving single-file movement in a circle shape or type constitute approximately 19% of the total single-file experiments. The initial research adopting the circle shape in single-file experiments is done by Jezbera et al. [7]. Subsequent studies have continued to perform circle experiments [9, 10, 14, 16, 22, 24, 32]. None of the researchers explicitly state the rationale behind choosing the circle over the oval configuration. Jezbera et al. [7] merely state that they chose a geometry allowing pedestrians to walk in a single line without overtaking, to perform experiments at various pedestrian densities, and to operate in closed boundary conditions. After reviewing the literature in oval and circle shapes, we summarize the main purpose of the experiments as presented in Table 2.

In ground-level experiments under closed boundary conditions, few researchers study single-file movement using the following setup shapes/types: a rectangle, a rectangle with four straight corridors and four arcs, and a square with four straight corridors and four arcs. Wang et al. [30] investigate the movement characteristics of pedestrians during the deceleration phase. The experimental setup employs a rectangular configuration; the rationale behind using a rectangular shape is not explicitly stated. This configuration consists of two horizontal and longitudinal paths. The authors emphasize the significance of understanding the deceleration phase in real-life scenarios, where pedestrians slow down to avoid collisions when their predecessors suddenly come to a stop. The focus of Wang et al.'s article is on examining different stop-distance commands: normal stop and close stop, for two types of walking speeds, namely normal and fast walking. Cao et al. [23] investigate the influence of the pedestrian's visibility on the movement properties in a rectangle with four straight corridors and four arcs setup. The authors perform three types of experiments under limited visibility: 0.3% (partial visibility), 0.1% (partial visibility), and 0.0% (no visibility) light transmissions. The shape of the setup has four straight corridors with three arcs built with longitudinal walls. These long walls serve as boundaries to ensure that participants remain within the experimental setup while walking with limited visibility.

Table 2: Summary of the objectives of oval and circular single-file experiments.

Main Objective	**Focuses**	**References**
Investigate movement characteristics or behavior	Distances between pedestrians	[7]
	Density-speed relationship	[1]
	Instantaneous velocity and spatial headway Relationship	[10]
	Microscopic movement characteristics (density-speed, lateral sway, step frequency, headway distances, and speed-headway distances)	[11]
	Stepping behavior (step length, step duration, stepping synchronization, step extent, and contact buffer)	[19, 34, 54]
	Movement in high-density conditions	[24]
	Influence of bottlenecks on pedestrian flow	[55]
Validate data extraction methods	Trajectories of pedestrians' heads	[6]
Effect of influential factors	Rhythm	[9, 16]
	Instructions (walking decisions in crowds)	[22]
	Social conventions and location	[2, 41]
	Age	[12, 25]
	Gender	[26, 39, 56]
	Background music	[28]
	Height constraints	[29]
	Social distancing measures	[33]
Compare traffic systems	Cars vs. bicycles vs. pedestrians	[14]
Compare data sources	Experiments vs. field studies	[17]
Compare setup shapes	Oval vs. circle	[32]

From reviewing the ground-level experiments, we observe that the selection of open or closed shapes/types depends on the goal of limiting the number of pedestrians inside the experimental setup and achieving high density without encountering boundary effects. Additionally, it depends primarily on the *purpose of the experiment*. For example, Lian et al. [37] aims to investigate the effect of complex structures (pedestrians merging on branching walking paths) on the properties of pedestrian movement. Another experiment by Seyfried et al. [1], where they execute an oval setup to analyze the simple system of pedestrians walking at different densities and without boundary effect. However, some researchers do not explicitly state the reason for choosing the shape/type of the experimental setup, but we can deduce it based on the experimental information and details provided.

In summary, we offer valuable insights and recommendations derived from a comprehensive review of the literature on the shapes of setups and experimental settings. We recommend having fewer variables in the experimental settings. That emphasizes isolating undesired effects from the surrounding environment, including external sounds, weather changes, and light changes. Any variation in the experiments can impact the way pedestrians walk. Some research already examines the potential effect of the setup configuration (oval and circle) on pedestrian movement [1, 8, 32]. The oval setup consists of two straight parts and two curvatures, whereas the circular setup is entirely composed of a continuous curve. Seyfried et al. [1] consider the possible influence of the curve part of the oval setup. To avoid this effect, they widen the width of the corridor in the curves, and a measurement section is selected in the center of the straight part of the passageway. However, we assume that limiting the investigation only to the straight part will neglect the characteristics that could be explored in the entire walking path. To avoid the previous issue, Ziemer et al. [13] proposes transforming the oval trajectories into straight trajectories. In this case, the investigation of all trajectories is applicable.

From observing some oval experimental videos, we notice that the navigation between the two parts (straight and curved) could be responsible for a change in walking behavior because the pedestrian turns at the beginning of the curve. The study of [13] already assumes the potential influence and compares the fundamental diagram relationship (density-speed) of the straight and curved parts. They use the Kolmogorov-Smirnov test to determine whether two data sets in the density-speed relationship have the same distribution. The results show that the difference between the straight and curved parts can be neglected.

Fu et al. [32] have another opinion about the possible influence of the curve. The authors examine the impact of curvature by comparing oval and circular pedestrian experiments while keeping settings like path circumference, participant number, methods to extract trajectories, movement direction, and measurement techniques constant. They find that pedestrian flow in the straight part of the oval setup is 20% higher than in the curved part of both setups. This difference is attributed to a more heterogeneous distribution on straight paths, allowing efficient space use and increased flow, whereas curvature leads to a more homogeneous distribution and reduced density. Additionally, at high global densities, the mean instantaneous density is higher in the oval passage than in the circular one. The curvature effect causes differences in pedestrian distribution and decreases density. These findings highlight significant differences in movement characteristics between oval and circular setups. Therefore, we advise researchers studying experiments involving curves to either standardize turning angles for experiments that aim to compare or use experiments with similar shapes.

4 Data Collection

This section provides an overview of the data collection processes for pedestrians' single-file experiments conducted under closed-boundary conditions. This section does not explore the devices suitable for data collection in achieving the experiment objectives. However, we provide an overview of the data collection processes in the literature, the data types, and the devices used to collect data from single-file experiments. For more details, we refer to Table 4 in Appendix B

We define *data collection* in single-file experiments as a systematic process for collecting and processing data to investigate the characteristics of pedestrian motion. Several data collection processes are followed depending on the *data type, devices, and methods* used for data collection. The process mainly includes the following steps: installing the devices to collect data (i.e., capturing videos and detecting brain signals) and processing the data (e.g., extracting head positions by detecting pedestrians' heads and tracking them throughout the experiment duration). Based on the experiments we review, the data collection processes can be categorized into two groups:

1. **Semi-automatic data collection**: combines both manual and automatic processes. In other words, some tasks or functions in the data collection processes are automated, while others require human intervention. For instance, Chattaraj et al. [2] use a digital camera to capture the experiments and manually extract the data frames of participants entering/exiting from the measurement area by observing the videos.

2. **Automatic data collection**: all processes are fully automated. The only involvement of humans is to verify and manually adjust the results from the system. For example, Paetzke et al. [39] capture the whole experiment using a digital camera and then detect and extract pedestrians' heads using PeTrack [57] software.

The first step in the data collection involves employing the *appropriate devices* to collect data required for the investigation. In single-file experiments, various devices are installed to collect data and differ in the type of data they measure (see Figure 4).

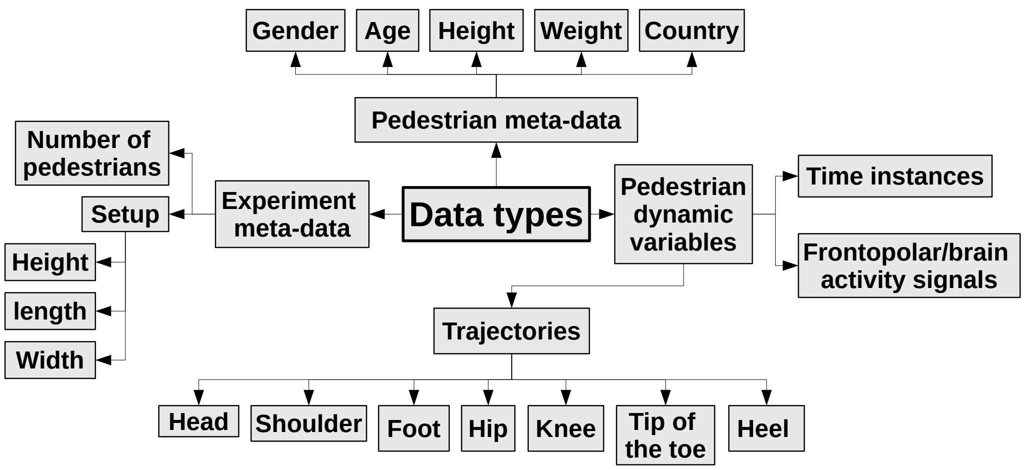


Figure 4: The data types presented in the single-file movement articles (under closed-boundary conditions) from the literature in this article.

The primary focus of most experiments is to capture pedestrians' positions over time through *head trajectories* [5, 6, 11–14, 19, 21–26, 28–30, 32, 33, 39, 40, 58], which is significant for calculating movement quantities such as speed, density, and headway distances. *Cameras* are the predominant devices used to collect head trajectories. The cameras capture video footage, enabling the extraction of trajectories by detecting and tracking the positions throughout the experiment execution. This results in 2D or 3D positions over time. Various types of cameras are utilized for this purpose. The most commonly used are the *digital cameras* to capture the experiment from a side-view [1, 5, 38] or bird's-eye view [6, 11–14, 19, 21, 23, 25, 28–30, 32, 33, 37, 39, 58]. The former condition (side-view) is recommended when the roof of the experimental hall is not high enough to locate the camera perpendicular to the setup, or if the researchers are interested in observing the movement characteristics from the side view. Whereas, the latter condition (bird's-eye view) provides the data of the overall periodic movement of all pedestrians inside the entire setup. Other types of cameras used rarely in the experiments include *Stereo Vision camera* [1], *UAV drone camera* [24], *infrared camera* [10, 22], and *Camcorders device*. [34].

More types of data are extracted from video footage. Thompson et al. [38] collect trajectories of shoulders, *hips*, *knees*, *tips of the toes*, and *heels* to analyze stepping behavior. Furthermore, *time instances* of entry/exit to/from a specified measurement area are recorded to calculate the density in [1, 2, 5, 17, 41]. Other devices are less commonly used in the literature for extracting movement data, such as the *light gate* [7] detect each pedestrian's crossing time at a designated spatial point, ultra-small near-infrared spectroscopy *(NIRS)* device [16] to measure *frontopolar/brain activity signals*, and *Ultra-Wideband (UWB)* to collect pedestrians' trajectories by utilizing tag signals combined with the location coordinates of the base station [40]. After reviewing the literature, we include that the selection of data collection devices depends on the types of data one aims to measure or record to investigate quantities related to movement. Besides, this choice is influenced by the researchers' preferences, which are shaped by the availability of both experience and financial resources to explore and implement new, specialized devices.

The second step for collecting data involves the *processing of the collected data*. It includes extracting the data of interest from collected raw data (i.e., video footage) and preparing the data for usage. One of the most common processing steps for video footage is the extraction of pedestrians' head trajectories over the experimental duration. To achieve this, the process begins by detecting individuals' heads or markers in the initial frame and then tracks their positions in subsequent frames. In addition to the videos, there are other data types, such as pedestrian information stored in an ID marker [39]. Several methods employed in the literature to process the data, such as *manual observation* of the videos [1, 17, 41], applying image processing techniques based on the *mean-shift algorithm* [19, 23, 33, 37], *Tracker software* [24], and *PeTrack software* [5, 12, 21, 25, 26, 28–30, 32, 39]. PeTrack [57] is the widely used open-source software in the literature because it is specialized software for calibrating, recognizing, and tracking pedestrians and is available online for free. Based on our literature review, we conclude that the data processing varies depending on the utilization of collected data in the investigation (i.e., calculating movement quantities using pedestrian positions).

5 Movement Quantities

After collecting the data, the quantities that characterize pedestrian dynamics are calculated. The researchers use these quantities to quantitatively analyze pedestrian dynamics. In this section, we narrow the focus to the research on ground-level experiments conducted under closed boundary conditions. We discuss the quantities and the methodologies employed.

We can categorize the movement quantities in the literature into four groups based on their focus on different aspects of human behavior: quantities to describe *head movement* (to represent pedestrian movement) [1, 2, 6–8, 10, 12–14, 17, 22–26, 29, 30, 32, 33, 39, 41, 55, 56, 58], *stepping locomotion* [9, 19, 21, 34, 38, 54], *both* (head movement, stepping locomotion) [11, 28], and *cognitive behavior* (using brain signals) [16]. Here, we focus the review on the research that analyzes head movement.

Different methodologies are employed in the literature to calculate movement quantities. These methodologies vary according to the objectives of the analyses. The first aspect is the level of movement to describe, including *microscopic* [12, 13, 26, 30, 31, 33, 37, 39] and *macroscopic* levels [1, 2, 28, 41]. At the microscopic level, the movement properties of each pedestrian are investigated during the experiment. At the macroscopic level, the motion characteristics of a group of pedestrians are studied throughout the experiment and averaged over time or space. Jelic et al. [10] qualitatively analyze the influence of different measurement procedures—macroscopic and microscopic—which they refer to as global and local measurements, respectively. Comparing the density–speed diagrams from both measurements reveals very similar results at low densities (approximately less than 1.2 m^{-1}). At higher densities (when stop-and-go waves appear), the results of both measurements differ. Ren et al. [25] find that both macroscopic and microscopic level measurements reveal similar trends in density-speed diagrams but with different levels of resolution. The microscopic level measurements provide finer detail, particularly at higher densities, where localized fluctuations in speed and density become pronounced. We observe from reviewing the literature that using macroscopic measurements, where the movement quantities are averaged for multiple pedestrians, ignores the individual movement characteristics. Further quantitative research is needed to compare the disparities in the results from various measurement procedures in single-file experiments. Previous studies show that different measurement procedures produce varying density–speed relations [59]. However, these findings are based on studies of crowds in straight corridors and T-junction experiments, not on single-file movements.

The second aspect is the setup area that the measurements cover. Studies focus on either the *measurement area* (a predefined part of the experimental setup) [2, 23, 26, 28, 29, 32, 33, 39, 41], or the *entire setup path* (applying a linear transformation or 2D calculations) [12, 13, 25, 28]. Upon reviewing the literature, we notice that calculating movement quantities for a specific part of the setup is simpler. It is simple because there is no need to transform the trajectories when analyzing longitudinal movement (along the x-axis). Instead, the equations for calculating quantities are applied directly to that area. We discuss this further in Section 7. However, analyzing pedestrian movement across the entire setup enables observing phenomena like stop-and-go waves that require complete trajectories [13].

The third aspect is the dimension for calculating movement quantities: *one dimension* or *two dimensions*. Most studies focus on the 1D movement because the researchers are interested in studying the longitudinal interactions among pedestrians walking in single-file experiments. Only Fu et al. [32] calculate the speed and density in 2D in the circle experiments without reporting why they used the 2D measurements. Yet, no single-file research compare the analysis results using 1D and 2D measurements. Using data from Paetzke et al. [39] experiments, we plot the speed-density relation to observe the differences between 1D and 2D measurements (using the tool in Section 7). We disregard comparing density in one and two dimensions because the 2D density values are equivalent to the 1D values plus a constant. As we see in Figure 5, the volume of speed in 2D is larger than 1D, because the magnitude of the speed in 2D is inherently greater than 1D. The significance of this difference can be further investigated, depending on quantitative analysis and the objective of the experiment (i.e., is the lateral displacement of the head important for the research?).

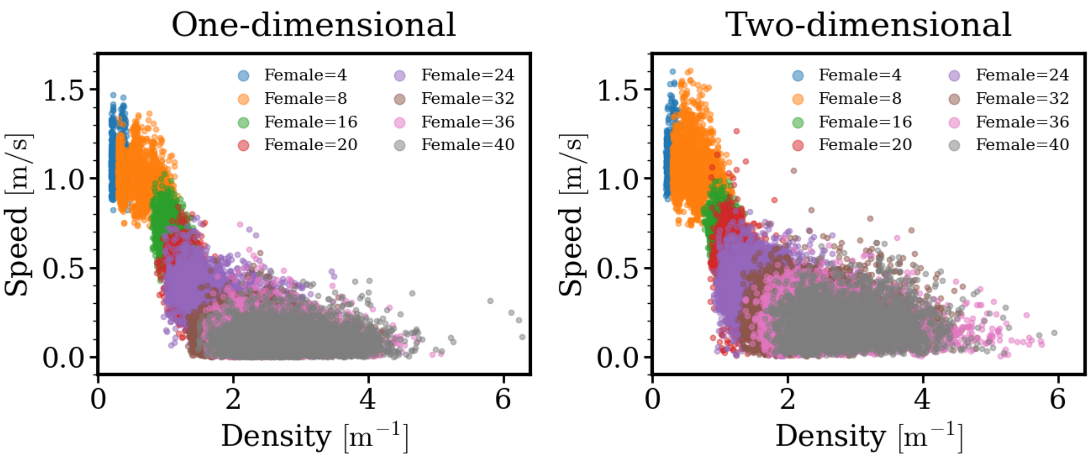


Figure 5: Speed-density relation using 1D and 2D measurements of the speed.

The fourth aspect concerns the *phase of movement chosen for analysis*. In single-file experiments, Chattaraj et al. [2] identify three distinct phases of movement: *acceleration*, during which pedestrians start walking and their speed increases gradually; *steady state*, where their speed remains relatively stable; and *deceleration*, in which individuals gradually reduce their speed until they leave the setup or stop. Most studies focus on investigating movement characteristics during the steady state, except Wang et al. [30]. In the latter, the authors study how people slow down when walking in single-file to better understand their behavior during sudden stops [30]. The author's motivation for conducting this study is to enhance evacuation plans, prevent collisions, and ensure safety during emergencies. We believe that analyzing the data from a steady state allows gaining valuable insights into system behavior while simplifying the analysis. However, we assume it is essential to recognize the limitations of steady-state analysis and consider transient effects when necessary for a comprehensive understanding of pedestrian dynamic systems.

Finally, we summarize an artifact related to the calculation of movement quantities that influence single-file movement analysis as reported in the literature. Jelic et al. [10] demonstrate that the number of *detected markers* during data extraction affects the analysis. Some pedestrians' head markers are occluded in the experimental videos resulting in the loss of their head trajectories during specific time intervals. Jelic et al. compare the density-speed relationship using different numbers of detected markers and find that data points for all marker quantities mostly overlap. Additionally, density values are higher with fewer detected markers because density calculations include distances between pedestrians and their predecessors and followers. Hidden predecessors or followers not included in the trajectories increase these distances. We recommend that the position and numbers of detected markers match the real experiment's precision to avoid inaccuracies in the analysis.

6 Factors that influence movements

Various factors can be examined in pedestrians' single-file experiments (see Figure 7). In this section, we focus on discussing the influential factors already investigate on the ground-level evacuation scenario under closed-boundary conditions. We categorize these factors and discuss their influence on the characteristics of pedestrian movement.

Analyzing the impact of various influential factors is essential for modelers simulating pedestrian movement and for event organizers to implement safety procedures. To understand pedestrian walking behavior, we thoroughly explore potential factors and their impact on movement quantities, such as speed changes and flow variations. Analyzing these factors helps uncover correlations and causal relationships between variables, which are important for defining movement.

By observing experimental videos, participating in experiments, reviewing relevant literature, and conducting research on diverse aspects of single-file movement, we categorize these influential factors into three main groups based on their sources (see Figure 6):

- **Personal attributes** such as age, gender, etc.
- **Cognitive factors** involve mental processes and knowledge acquisition through thoughts, experience, and the senses, i.e., route choice, and motivation.
- **Social factors** including interactions with other pedestrians.
- **Environmental factors** including physical characteristics and layout of the experiment where individuals move and interact, such as location, weather, lighting conditions, etc.

We define *social conventions* as a set of agreed-upon or generally accepted standards and social norms that a group of people follows. These conventions influence walking behavior, as observed by Chattaraj et al. [2] in their pioneering research comparing young German and Indian participants. They conduct quantitative and qualitative analyses of the free-flow speed, density-speed, and speed-headway relations of Indian and German experiments. The results show that German walking speed is more dependent on density than Indian speed, with Indian data exhibiting greater fluctuations in speed and density (unordered behavior). Germans maintain greater personal space (headway distance) than Indians. Furthermore, both groups have similar free-flow speeds when walking alone. Bilintoh et al. [41] also examine social conventions by studying the *locations* of compatriots in single-file experiments conducted in Ghana and China with African students. They compare movement characteristics such as density, speed, flow, and headway. Their analysis reveals that Ghanaian pedestrians (speed between 0.74 ± 0.01 m/s and 0.32 ± 0.02 m/s) walk slower than the African students in China (speed between 1.11 ± 0.01 m/s and 0.31 ± 0.03 m/s) at the same global densities of 0.62 m^{-1} and 0.95 m^{-1}, respectively. Additionally, Ghanaians maintain smaller personal space than African students in China based on headway distances.

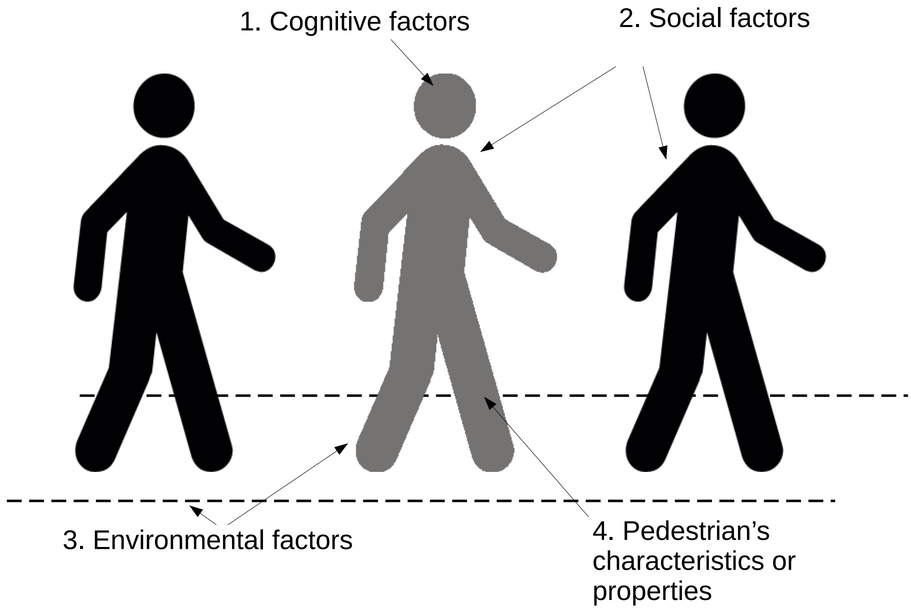


Figure 6: Main groups of factors that Influence movement in single-file experiments as proposed by the authors

Age and gender are *personal attributes* influencing movement. Ren et al. [25] and Cao et al. [12] investigate the *age* effect on pedestrian dynamic. Cao et al. conduct a comparative analysis of homogeneous and heterogeneous age groups, including youth (16-18 years, average age 17), old adults (45-73 years, average age 52), and mixed groups (youth and elders randomly ordered). In contrast, Ren et al. focus on elders aged 50-85 years, with an average age of 70. Cao et al. find that young students move faster than old adults in the speed-density relationship. At the same density, the young group is faster than the mixed group. The mixed group's speed is slightly lower than that of the old adults' group at densities between 0.5 m^{-1} and 1.2 m^{-1}, while it is higher at densities below 0.5 m^{-1}. Additionally, flow increases monotonically with density for all groups but reaches different peak flows: 1.3 s^{-1} for youth, 0.9 s^{-1} for old adults, and 0.7 s^{-1} for mixed groups around a density of 0.9 m^{-1}. Ren et al. compare the speeds of elders and old adults, finding that the elders walk slower than the adults in the low-density scenarios but at roughly the same speed in the mixed group. Furthermore, stop-and-go waves occur frequently and last for a longer duration in the elderly group compared to the old adult group. The authors observe from the experiment videos, time-space diagrams, and headway values that some elders wait several seconds until they have a certain sufficient distance in front to move again. Elders do not resume walking synchronously with the preceding pedestrian after stopping, a phenomenon they term "active cease". We attribute these differences in movement to the physical mobility capabilities of pedestrians.

In *gender* studies, Subaih et al. [56] and Paetzke et al. [39] explore the impact of gender composition on pedestrian movement. While their objectives are similar, their contributions and findings differ. Both studies use statistical analyses to assess the significance of their findings with different testing methods. They find that homogeneous gender groups (either all female or all male) exhibit similar density-speed relationships. Subaih et al. observe differences in the density-speed diagram between homogeneous and heterogeneous (mixed-ordered) gender groups, suggesting that the gender of neighboring pedestrians affects movement. In contrast, Paetzke et al. expand the analysis to various group compositions and find that gender composition effects on speed-density relations are either nonexistent or only present within a narrow density range. They attribute these discrepancies to different statistical methods and data preparation. Furthermore, Paetzke et al. investigate additional factors like *weight*, *height*, and the gender of the preceding pedestrian but conclude that these factors do not significantly improve the predictability of pedestrian speed. This reinforces that gender composition and these additional factors have minimal impact on pedestrian dynamics in single-file movement.

Some influential factors are controlled or manipulated to observe their effects on the experimental results (*motivation*). For example, organizers use instructions, music, and environmental changes to assess their impact on participants' behavior and walking patterns. Lu et al. [33] investigate pedestrian movement under different *social distancing measures* similar to those during COVID-19 in China: 1 m, 2 m, and normal conditions (before COVID-19). They find that social distancing measures caused participants to maintain greater distances than normal conditions, though some violations occurred. Stop-and-go waves under social distancing measures are observed not only at high densities but also at low-density ranges. We suppose the reason is that pedestrians prefer to stay alert and maintain the predefined distance to follow the instructions. Thus, they stop to estimate and adjust the distance headway before proceeding. Wang et al. [30] investigate the effect of *stop distances* by instructing participants to either stop close to or normally behind their predecessors. The close-stop condition results in shorter average stop distances (0.34 m) compared to normal stops (0.63 m). Additionally, the speed-distance headway slope is steeper in close-stop experiments, indicating more abrupt deceleration as participants approach the person in front.

Appert-Rolland et al. [22] study the *cognitive processes* of pedestrians, focusing on how increased freedom of movement affects pattern formation, interaction, and decision-making in crowds using a single-file system. In their experiments, participants are instructed to walk in a self-chosen virtual circle without predefined boundaries. Consequently, participants form circular paths by following and interacting with their predecessors (following behavior).

Another group of researchers focuses on the influence of *music, songs, and metronome* rhythm on pedestrian motion. They hypothesize that music and rhythm enhance pedestrian flow in congested situations without causing danger. Zeng et al. [28] perform an oval experiment to understand the impact of background music on movement. Seven experiments are performed: three with different music tempos, three with rhythms from a metronome device, and one without music (normal conditions). The authors only analyze and compare the movement under normal conditions and with music at 120 beats per minute (BPM). The analysis of density-speed and density-flow shows that at the medium and high densities investigated, speed and flow are lower with background music than under normal conditions. Stop-and-go waves appear in both cases at a global density of $\rho_{\text{glob}} = 1.82\ \text{m}^{-1}$, but with background music participants stop frequently and for a longer duration.

In studying the impact of metronome rhythm, Yanagisawa et al. [9], Ikeda et al. [16], and Li et al. [40] conduct experiments with different types of setups with and without a rhythm of 70 BPM. Yanagisawa et al. use experimental data to validate their pedestrian flow model, which combines two primary parameters: step size and walking pace (steps per unit time). Their results indicate that the slower walking rhythm can enhance pedestrian flow in congested environments. This improvement occurs because pedestrians maintain a more consistent pace and avoid abrupt reductions in step size, which is observed in the experimental data. Specifically, the slow rhythm helps synchronize pedestrian movement, reducing variability and improving flow at high densities.

Ikeda et al. analyze the impact of steady beats on the cognitive processes of pedestrians by measuring participants' frontopolar brain activity in walking and stepping groups. They find that playing a steady beat sound (like a metronome) helps groups walk together more smoothly in crowded situations and improves the coordination between their brain activities, particularly in the prefrontal region. The aforementioned research on music and metronome rhythms demonstrates that pedestrian flow can be improved by music and rhythm, which influence stepping behavior and cognitive processes.

There are also *Environmental factors* that significantly impact pedestrian movement, as demonstrated by various studies. Cao et al. [23] investigate the movement under various *visibility conditions* by testing three levels of light transmission (0.3%, 0.1%, and 0.0%). The study show that pedestrian speed and flow change significantly with different visibility conditions. Specifically, the following behavior (toward proceeding pedestrians or the walls) is observed at light transmissions of 0.1% and 0.0%. Additionally, stop-and-go waves appear at low densities and increased as visibility decreased. The maximum specific flow rates vary with visibility, being 1.3 s^{-1}, 1.15 s^{-1}, and 0.9 s^{-1} for light transmissions of 0.3%, 0.1%, and 0.0%, respectively.

Chattaraj et al. [2] investigate the influence of *corridor length* and found no significant impact on speed-density or speed-headway distance relations. Jelic et al. [10] analyze how the *walking path* -either along the inner wall or the outer wall of a circular setup- affects pedestrian movement. The authors observe that pedestrians maintain a slightly greater distance from the wall when walking along the outer path compared to the inner path. Furthermore, they find no significant differences in density-speed relations between the two paths.

Ren et al. [25] explore the effects of *vertical walls* in various experimental setups, observing different pedestrian behaviors based on wall presence. They examine three cases: case one with a wall on one side of a straight section, case two with walls on both sides of a straight section, and case three with no walls in curved sections. Pedestrians in case one tend to walk away from the wall towards the open side, while movements in case two are less fluctuating and more concentrated compared to cases one and three. In case three, fluctuations are more frequent, and pedestrians often crossed boundaries, especially at high densities, leading to overlapping. The study concludes that boundary types, whether vertical walls or ground tape, significantly affect pedestrian movement characteristics. Ren et al. [25] also observe the influence of the *setup shape* on the speed of pedestrians (straight and curved). This influence is further analyzed by Fu et al. [32], where the authors find that pedestrian flow increases in the straight part (oval experiments) than the flow in the curve part (discussed before in Section 3).

Ma et al. [29] conduct experiments to understand the impact of *height constraints* (1.0 m, 1.2 m, 1.4 m, 1.6 m, and 2.0 m) on pedestrian movement. The authors find that speed distributions across different heights follow a Gaussian pattern, with lower height constraints significantly reducing pedestrian speeds and altering the flow. In conclusion, experimental settings such as visibility, corridor length, walking path, boundaries, setup shape, and height constraints significantly affect pedestrian movement analysis. These factors should be carefully considered in the analysis and interpretation of results.

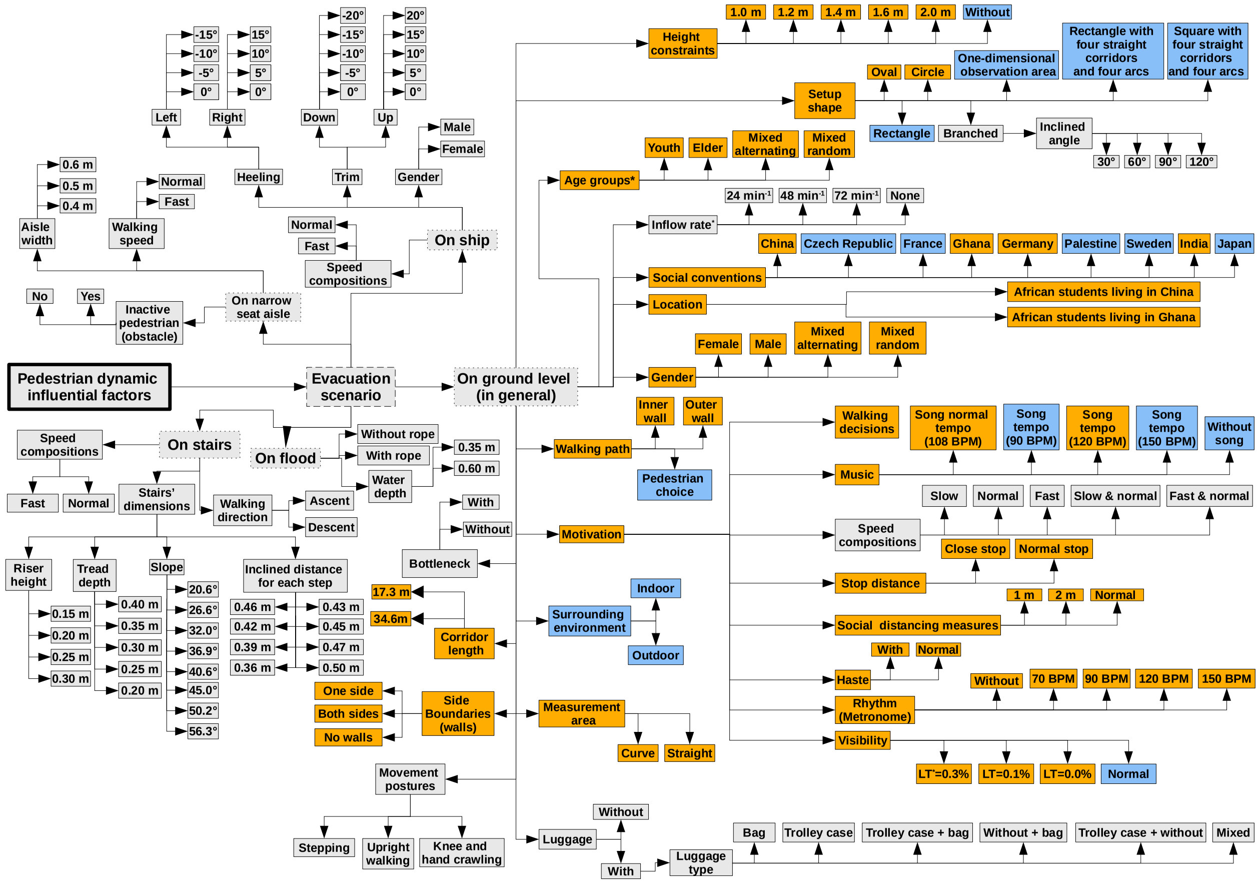


Figure 7: Categories of factors influencing the movement in single-file experiments from the literature. Arrows indicate the categories of influential factors concerning the evacuation scenario, and the influential factors along with lists of quantitative or categorical variables for comparison. Orange denotes factors studied under closed boundary conditions at ground level, while blue represents factors assumed to affect the movement (by the authors).

7 Methodology for Preparing Trajectory Data and Calculating Movement Quantities

From reviewing the literature, we notice that various studies employ different codes and tools to analyze experiments. These differences stem from diverse experimental setups and settings. We analyze data from multiple studies to ensure a comprehensive understanding, i.e., comparing the one-dimensional and two-dimensional measurements discussed in Section 5. We identify the need for foundational software for single-file experiments that researchers can build upon. This software is open-source and available online, enabling developers to systematically analyze experiments across different settings. The tool serves as a standardized approach for data analysis. Furthermore, it provides a foundation for future development, allowing other researchers to enhance its capabilities by adding new features.

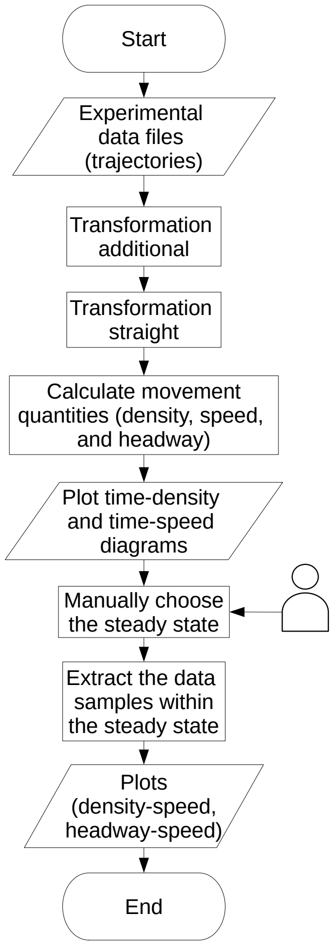


Figure 8: Flowchart for calculating movement quantities using head trajectories.

In this section, we introduce a Python tool for analyzing single-file experiments. We also propose a methodology for preparing experimental data (head trajectories), calculating movement quantities, and analyzing the common relations investigated in the single-file literature: density-speed and density-headway. To qualitatively and quantitatively analyze the single-file movement by using head trajectories, we propose the methodology outlined in the flowchart presented in Figure 3 to prepare the raw data and calculate movement quantities.

The first two steps in the methodology for preparing the raw trajectory data are *transformation additional* and *transformation straight*. Upon observing the plots of raw trajectories in the literature, we notice that the (x, y) values are centered around different points, depending on the trajectory extraction process (location of the coordination system). To convert oval trajectories into straight - a process we refer to as the "transformation straight" step, following the method of Ziemer et al. [13] - we adjust the trajectories to a new, unified Cartesian coordinate system, $T : \mathbb{R}^2 \to \mathbb{R}^2, \begin{pmatrix} x \\ y \end{pmatrix} \mapsto \begin{pmatrix} x' \\ y' \end{pmatrix}$.

In this system, trajectories represent a person starting her/his walk from the beginning of the bottom straight corridor ($x = 0$), along the corridor's central line ($y = 0$) (Sub-figure I.9(b) show the new coordination system). *Additional transformation* is achieved by applying appropriate transformations in geometry, such as rotation, shifting, etc (see Sub-figures I.9(a) transform to I.9(c)).

Some common cases for additional transformation are summarized as follows:

1. In some experiments, the (x, y) coordinates are given in centimeters. We convert them to meters by setting the unit conversion factor u as follows: if the original units are in centimeters, then $u = 100$ to convert to meters; otherwise, $u = 1$.

2. To ensure the straight segments of the oval setup are parallel to the x-axis, rotate the trajectories by 90° clockwise, transforming $(x, y) \to (y, -x)$, or 90° anticlockwise, transforming $(x, y) \to (-y, x)$. For experiments, pedestrians walk either clockwise or anticlockwise. In clockwise experiments, apply horizontal reflection to calculate distances, setting constraints $i = -1$ and $j = -1$ for axis reflections; otherwise, set $i = 1$ and $j = 1$.

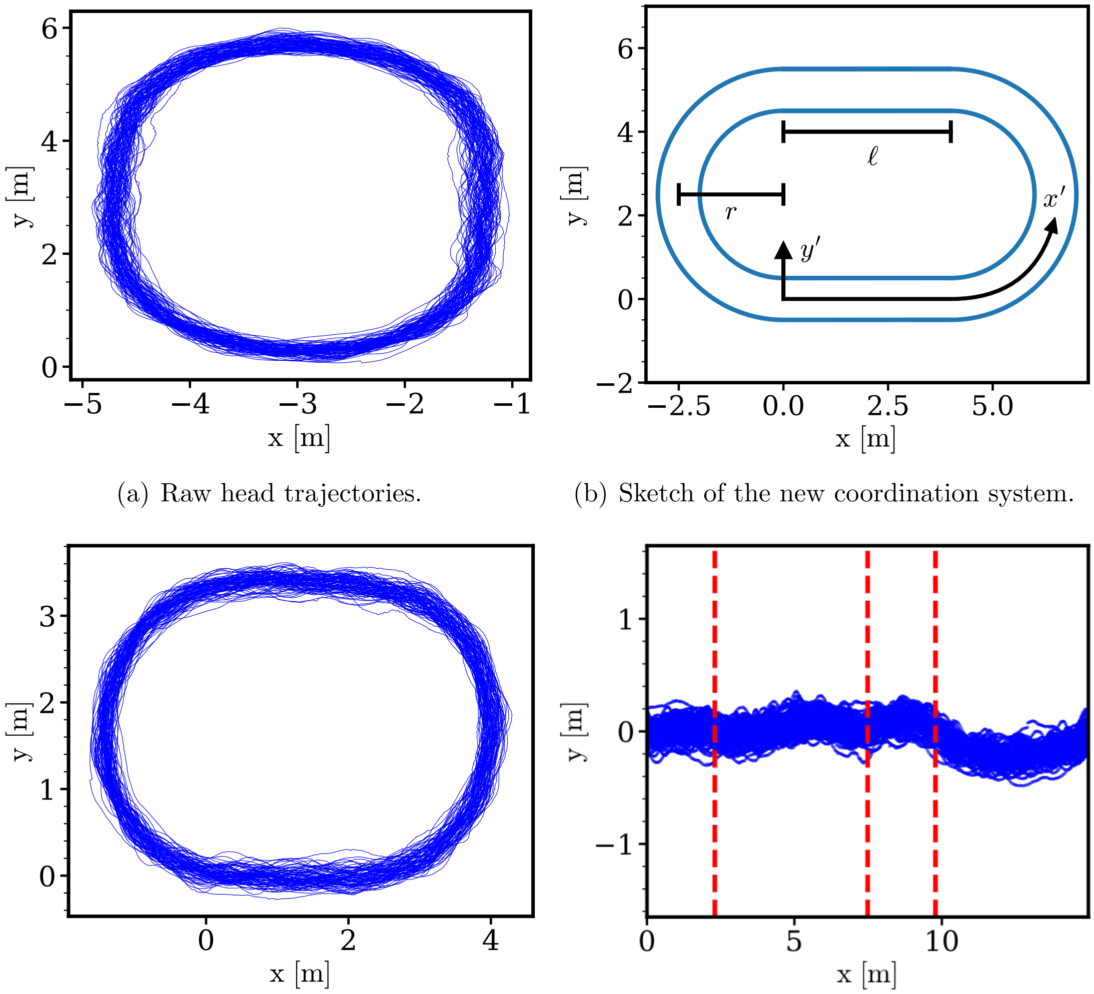
3. To align the origin with the middle line of the corridor, as shown in Sub-figure I.9(b), we need to shift the trajectories horizontally or vertically. For horizontal and vertical translations, we use the constants $k \in \mathbb{R}$ and $d \in \mathbb{R}$, respectively.

The additional transformation equations T are:

$$x' = \frac{i.x}{u} + k. \tag{1}$$

$$y' = \frac{j.y}{u} + d. \tag{2}$$

In case we want to calculate the movement quantities for pedestrians walking inside a specific area (the straight part), we need to extract (x, y) values from within the space interval of the measurement area, $(x, y) \in [a, b]$, where $a \in \mathbb{R}$ and $b \in \mathbb{R}$ represent the minimum and maximum x-axis values, respectively.



(a) Raw head trajectories.

(b) Sketch of the new coordination system.

(c) Transformation additional.

(d) Transformation straight.

Figure 9: The steps of the transformation applied to the trajectory data extracted from the single-file experiment.

To apply *transformation straight*, $T' : \mathbb{R}^2 \to \mathbb{R}^2, \begin{pmatrix} x' \\ y' \end{pmatrix} \mapsto \begin{pmatrix} x'' \\ y'' \end{pmatrix}$, the equations are defined as follows:

$$x'' = \begin{cases} \ell + r \arccos\left(\frac{r-y}{\sqrt{(x-\ell)^2+(y-r)^2}}\right) & x > \ell, \\ x & 0 \leq x \leq \ell,\ y < r, \\ 2\ell + r\pi - x & 0 \leq x \leq \ell,\ y \geq r, \\ 2\ell + r\pi + r \arccos\left(\frac{-r+y}{\sqrt{x^2+(y-r)^2}}\right) & x < 0, \end{cases} \tag{3}$$

and

$$y'' = \begin{cases} \sqrt{(y-r)^2} - r & 0 \le x \le \ell, \\ \sqrt{(x-\ell)^2 + (y-r)^2} - r & x > \ell, \\ \sqrt{x^2 + (y-r)^2} - r & x < 0, \end{cases} \tag{4}$$

where ℓ represents the length of the straight segment of the oval corridor, and r denotes the radius of the curved part (see Figure I.9(b)).

The third step of the methodology involves calculating the movement quantities. In our paper, we calculate *Voronoi 1D density*, *individual instantaneous speed*, and *headway distance*. To calculate the *headway distance*, we apply the following equation:

$$h_i(x) = \begin{cases} x_{i+1}(t) - x_i(t) & i = 1, ..., n-1, \\ (c - x_n(t)) + x_1(t) & i = n. \end{cases} \tag{5}$$

where n is the number of pedestrians in the experiment and c is the geometry circumference.

Voronoi 1D density is defined as:

$$\rho_i(x) = \begin{cases} \frac{2}{h_{i-1}(x)+h_i(x)} & x \in [\frac{h_{i-1}(x)}{2},\ \frac{h_i(x)}{2}[, \\ 0 & \text{Otherwise.} \end{cases} \tag{6}$$

Finally, we calculate the *individual instantaneous speeds* of pedestrians using the following equation for *side-view experiments* or analysis within a specific measurement area:

$$v_i(t) = \begin{cases} \frac{x_i(t+\Delta t/2) - x_i(t-\Delta t/2)}{\Delta t} & t + \Delta t/2 \le t_{\text{end}},\ t - \Delta t/2 \ge t_{\text{start}}, \\ \frac{x_i(t_{\text{start}}) - x_i(t-\Delta t/2)}{t - t_{\text{start}} + \Delta t/2} & t + \Delta t/2 > t_{\text{end}},\ t - \Delta t/2 \ge t_{\text{start}}, \\ \frac{x_i(t+\Delta t/2) - x_i(t_{\text{end}})}{t_{\text{end}} - t + \Delta t/2} & t + \Delta t/2 \le t_{\text{end}},\ t - \Delta t/2 < t_{\text{start}}, \\ 0 & \text{otherwise,} \end{cases} \tag{7}$$

where t_{start} and t_{end} are the time when the pedestrian i enters and leaves the measurement area, respectively. The short time constant of $\Delta t = 0.4$ s (10 frames) is used to smooth trajectories and avoid fluctuations in the stepping behavior of pedestrians. For the *top-view experiments*, Equation 7 (case one) is used to calculate the *1D* individual instantaneous speeds. In *2D*, the speed is calculated by dividing the displacement in 2D by Δt as follows:

$$v_i(t) = \frac{\sqrt{(x_i(t+\Delta t/2) - x_i(t-\Delta t/2))^2 + (y_i(t+\Delta t/2) - y_i(t-\Delta t/2))^2}}{\Delta t}. \tag{8}$$

For more details regarding the proposed analysis tool, check the GitHub project *SingleFileMovementAnalysis* [4]. The tool is tested across 10 experiments involving 28 datasets, as detailed in Appendix C, Table 5.

8 Summary, trends and future outlooks

In this section, we highlight the trends and the directions of future research in single-file experiments.

In single-file systems (discussed in Section 2), cars and bicycles are influenced by mechanical effects and inertia. This leads to systematic speed control and the maintenance of space to prevent collisions, especially in traffic jams. In contrast, animals such as mice and ants do not maintain personal space or time gaps and often overlap, pause randomly, and even move backward, resulting in higher flow at crowded densities. Pedestrians, like vehicles, maintain personal space, but like animals, their movements are flexible. At high densities, people slow down to avoid contact, creating stop-and-go patterns driven by psychological and physiological factors. These differences should be confirmed by further experiments.

In analyzing pedestrian movement, there is a clear consensus regarding the choice of experimental setups as reviewed in Section 3. Closed systems are preferred for investigating the fundamental diagram, as they provide controlled conditions that eliminate external boundary effects and control the density. In contrast, open systems are valuable for examining external influences, such as pedestrians' streams from different directions or decision-making in movement (i.e., direction to take, following behavior), which are critical in real-world scenarios. However, the influence of boundaries in these setups remains an area that requires further investigation. Understanding how boundary conditions affect pedestrian dynamics can enhance our comprehension of movement.

Data collection in pedestrian studies is develop to become more comprehensive, incorporating surveys that gather meta-data about pedestrians, such as demographic details and socio-psychological contexts. This trend reflects a growing recognition of the importance of understanding not only the physical movement of individuals but also the factors influencing their behavior. Furthermore, automation through tools like PeTrack has significantly advanced the precision of head trajectory extraction from videos, allowing for a more detailed analysis of pedestrian movement. Different types of data are extracted by Thompson et al. [38] such as the trajectories of shoulders, hips, knees, tips of the toes, and heels to improve the calculation of stepping quantities. By integrating this additional information, researchers can gain deeper insights into pedestrian dynamics and the various influences that shape movement in different environments. A new technologies to capture, track and analyze pedestrian steps, such as step extent and step frequency is required. In the literature, the measurements of stepping behavior are mostly analyzed using the head trajectories. This will enable researchers to improve accuracy and reduce errors in the analysis.

In Section 6, we discuss several factors that influence pedestrian dynamics which have already been investigated in the literature, categorizing them into personal attributes (age, gender), cognitive factors (route choice and motivation), social factors (interactions with others), and environmental factors (visibility and layout). Each of these factors significantly impacts, or does not, movement characteristics such as speed and flow, highlighting the complexity of pedestrian behavior. There is a growing interest in research examining the effects of rhythm and music on movement to improve the flow of pedestrians in congested situations. The researches [9, 16, 28, 40] highlight how the rhythm and music influence the fundamental diagram and the pedestrian behavior. Investigating how varying tempos affect coordination and flow in different environments may provide valuable insights into optimizing pedestrian movement, particularly in crowded settings where synchronization can enhance safety and efficiency. Future research could also explore the effect of the surrounding environment (indoor or outdoor) on pedestrian dynamics. Additionally, investigating the impact of emerging technologies, such as wearable devices that provide real-time data on movement, could further enhance our understanding of pedestrian dynamics. Finally, focusing on factors such as the role of individual cognitive processes and socio-psychological factors in pedestrian behavior. For example, how individuals feel under different motivations (e.g., evacuation, noise, rhythm) and how these factors influence their decision-making. More suggested factors are highlighted in Figure 7.

9 Conclusion

This article comprehensively reviews the literature on single-file pedestrian movement, with a focus on experiments and data analysis. We provide a scientific background and discuss the significance of single-file experiments in pedestrian dynamics. Then, we compare different traffic systems - including humans, mice, rats, bicycles, and cars - to highlight their similarities and differences. From this comparison, we derive insights that contribute to our understanding of pedestrian dynamics. Furthermore, we present a detailed discussion and categorization of the types of experimental setups, data collection methods, movement quantities, and influential factors of the movement, and provide our discussion. Finally, we propose a methodology and introduce the "SingleFileMovementAnalysis" tool for analyzing single-file pedestrian dynamics. After the comprehensive review, we recognize the ongoing need for further research in single-file movement. Specifically, experimental research focuses on the cognition processes of moving pedestrians to understand the related factors influencing the dynamics. We also suggest conducting research concerning defining and automating the steady-state in pedestrian single-file movement. Moreover, we encourage further experiments to investigate new influential factors and validate new data collection devices. There is still room for improvement in research on pedestrian single-file movement to compare experimental data against existing research objectively and easily, thereby improving the quality of analysis.

Acknowledgements The authors would like to thank Yi Ma, Guang Zeng, Jun Zhang, and Jian Ma for sharing their datasets of single-file experiments. Furthermore, we thank Tobias Schrödter for valuable feedback regarding the Python analysis tool. This work is supported by the German Federal Ministry of Education and Research (BMBF: funding number 01DH16027) within the framework of the Palestinian-German Science Bridge project. The authors acknowledge the Franco-German research project MADRAS founded in France by the Agence Nationale de la Recherche (ANR, French National Research Agency), grant number ANR-20-CE92-

0033, and in Germany by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation), grant number 446168800.

Author Contributions Rudina Subaih: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing –original draft, Writing – review & editing. Antoine Tordeux: Conceptualization, Writing – review & editing, Supervision. Mohcine Chraibi: Conceptualization, Writing – review & editing, Supervision.

References

[1] Armin Seyfried, Bernhard Steffen, Wolfram Klingsch, and Maik Boltes. “The fundamental diagram of pedestrian movement revisited”. In: *Journal of Statistical Mechanics: Theory and Experiment* 2005.10 (2005), P10002. DOI: 0.1088/1742-5468/2005/10/P10002.

[2] Ujjal Chattaraj, Armin Seyfried, and Partha Chakroborty. “Comparison of pedestrian fundamental diagram across cultures”. In: *Advances in complex systems* 12.03 (2009), pp. 393–405. DOI: 10.1142/S0219525909002209.

[3] Shuqi Xue and Nirajan Shiwakoti. “A meta-synthesis of experimental studies of pedestrian movement in single-file flow”. In: *Physica A: Statistical Mechanics and its Applications* (2023), p. 129255. DOI: 10.1016/j.physa.2023.129255.

[4] Rudina Subaih, Mohcine Chraibi, and Tobias Schrödter. *PedestrianDynamics/SingleFileMovementAnalysis: Comprehensive Review of Single-file Pedestrian Experiments*. Version v1.0.0. Apr. 2024. DOI: 10.5281/zenodo.10908397. URL: https://doi.org/10.5281/zenodo.10908397.

[5] Janine Lukowski. “Einfluss der Motivation auf das Fundamentaldiagramm der Fußgängerbewegung entlang einer Linie”. MA thesis. University of Wuppertal, 2009.

[6] Xuan Liu, Weiguo Song, and Jun Zhang. “Extraction and quantitative analysis of microscopic evacuation characteristics based on digital image processing”. In: *Physica A: Statistical Mechanics and its Applications* 388.13 (2009), pp. 2717–2726. DOI: 10.1016/j.physa.2009.03.017.

[7] Daniel Jezbera, David Kordek, Jan Kříž, Petr Šeba, and Petr Šroll. “Walkers on the circle”. In: *Journal of Statistical Mechanics: Theory and Experiment* 2010.01 (2010), p. L01001. DOI: 10.1088/1742-5468/2010/01/L01001.

[8] Armin Seyfried, Andrea Portz, and Andreas Schadschneider. “Phase coexistence in congested states of pedestrian dynamics”. In: *ACRI*. Springer. 2010, pp. 496–505. DOI: 10.1007/978-3-642-15979-4_53.

[9] Daichi Yanagisawa, Akiyasu Tomoeda, and Katsuhiro Nishinari. “Improvement of pedestrian flow by slow rhythm”. In: *Physical Review E* 85.1 (2012), p. 016111. DOI: 10.1103/PhysRevE.85.016111.

[10] Asja Jelić, Cécile Appert-Rolland, Samuel Lemercier, and Julien Pettré. "Properties of pedestrians walking in line: Fundamental diagrams". In: *Physical review E* 85.3 (2012), p. 036111. DOI: 10.1103/PhysRevE.85.036111.

[11] Weiguo Song, Wei Lv, and Zhiming Fang. "Experiment and modeling of microscopic movement characteristic of pedestrians". In: *Procedia Engineering* 62 (2013), pp. 56–70. DOI: 10.1016/j.proeng.2013.08.044.

[12] Shuchao Cao, Jun Zhang, Daniel Salden, Jian Ma, Ruifang Zhang, et al. "Pedestrian dynamics in single-file movement of crowd with different age compositions". In: *Physical Review E* 94.1 (2016), p. 012312. DOI: 10.1103/PhysRevE.94.012312.

[13] Verena Ziemer, Armin Seyfried, and Andreas Schadschneider. "Congestion dynamics in pedestrian single-file motion". In: *Traffic and Granular Flow'15*. Springer. 2016, pp. 89–96. DOI: 10.1007/978-3-319-33482-0_12.

[14] Yongxiang Zhao and HM Zhang. "A unified follow-the-leader model for vehicle, bicycle and pedestrian traffic". In: *Transportation research part B: methodological* 105 (2017), pp. 315–327. DOI: 10.1016/j.trb.2017.09.004.

[15] Juan Chen, SM Lo, and Jian Ma. "Pedestrian ascent and descent fundamental diagram on stairway". In: *Journal of Statistical Mechanics: Theory and Experiment* 2017.8 (2017), p. 083403. DOI: 10.1088/1742-5468/aa79ad.

[16] Shigeyuki Ikeda, Takayuki Nozawa, Ryoichi Yokoyama, Atsuko Miyazaki, Yukako Sasaki, Kohei Sakaki, and Ryuta Kawashima. "Steady beat sound facilitates both coordinated group walking and inter-subject neural synchrony". In: *Frontiers in human neuroscience* 11 (2017), p. 147. DOI: 10.3389/fnhum.2017.00147.

[17] Siddhartha Gulhare, Ashish Verma, and Partha Chakroborty. "Comparison of pedestrian data of single file movement collected from controlled pedestrian experiment and from field in mass religious gathering". In: *Collective Dynamics* 3 (2018), pp. 1–14. DOI: 10.17815/CD.2018.16.

[18] Shenshi Huang, Teng Zhang, Siuming Lo, Shouxiang Lu, and Changhai Li. "Experimental study of individual and single-file pedestrian movement in narrow seat aisle". In: *Physica A: Statistical Mechanics and its Applications* 509 (2018), pp. 1023–1033. DOI: 10.1016/j.physa.2018.06.079.

[19] Yi Ma, Ying Ying Sun, Eric Wai Ming Lee, and Richard Kowk Kit Yuen. "Pedestrian stepping dynamics in single-file movement". In: *Physical Review E* 98.6 (2018), p. 062311. DOI: 10.1103/PhysRevE.98.062311.

[20] Jinlu Sun, Shouxiang Lu, Siuming Lo, Jian Ma, and Qimiao Xie. "Moving characteristics of single file passengers considering the effect of ship trim and heeling". In: *Physica A: Statistical Mechanics and its Applications* 490 (2018), pp. 476–487. DOI: 10.1016/j.physa.2017.08.031.

[21] Jiayue Wang, Maik Boltes, Armin Seyfried, Jun Zhang, Verena Ziemer, and Wenguo Weng. "Linking pedestrian flow characteristics with stepping locomotion". In: *Physica A: Statistical Mechanics and its Applications* 500 (2018), pp. 106–120. DOI: 10.1016/j.physa.2018.02.021.

[22] Cécile Appert-Rolland, Julien Pettré, Anne-Hélène Olivier, William Warren, Aymeric Duigou-Majumdar, Etienne Pinsard, and Alexandre Nicolas. "Experimental Study of Collective Pedestrian Dynamics". In: *Collective Dynamics* 5 (2020), pp. 1–8. DOI: 10.17815/CD.2020.109.

[23] Shuchao Cao, Peng Wang, Ming Yao, and Weiguo Song. "Dynamic analysis of pedestrian movement in single-file experiment under limited visibility". In: *Communications in Nonlinear Science and Numerical Simulation* 69 (2019), pp. 329–342. DOI: 10.1016/j.cnsns.2018.10.007.

[24] Cheng-Jie Jin, Rui Jiang, Ruiwen Li, and Dawei Li. "Single-file pedestrian flow experiments under high-density conditions". In: *Physica A: Statistical Mechanics and its Applications* 531 (2019), p. 121718. DOI: 10.1016/j.physa.2017.08.031.

[25] Xiangxia Ren, Jun Zhang, and Weiguo Song. "Contrastive study on the single-file pedestrian movement of the elderly and other age groups". In: *Journal of Statistical Mechanics: Theory and Experiment* 2019.9 (2019), p. 093402. DOI: 10.1088/1742-5468/ab39da.

[26] Rudina Subaih, Mohammed Maree, Mohcine Chraibi, Sami Awad, and Tareq Zanoon. "Gender-based insights into the fundamental diagram of pedestrian dynamics". In: *Computational Collective Intelligence: 11th International Conference, ICCCI 2019, Hendaye, France, September 4–6, 2019, Proceedings, Part I 11*. Springer. 2019, pp. 613–624. DOI: 10.1007/978-3-030-28377-3_51.

[27] Shenshi Huang, Ruichao Wei, Siuming Lo, Shouxiang Lu, Changhai Li, Chao An, and Xiaoxia Liu. "Experimental study on one-dimensional movement of luggage-laden pedestrian". In: *Physica A: Statistical Mechanics and its Applications* 516 (2019), pp. 520–528. DOI: 10.1016/j.physa.2018.09.038.

[28] Guang Zeng, Andreas Schadschneider, Jun Zhang, Shibo Wei, Weiguo Song, and Rui Ba. "Experimental study on the effect of background music on pedestrian movement at high density". In: *Physics Letters A* 383.10 (2019), pp. 1011–1018. DOI: 10.1016/j.physleta.2018.12.019.

[29] Jian Ma, Dongdong Shi, Tao Li, Xiaofei Li, Tengfei Xu, and Peng Lin. "Experimental study of single-file pedestrian movement with height constraints". In: *Journal of Statistical Mechanics: Theory and Experiment* 2020.7 (2020), p. 073409. DOI: 10.1088/1742-5468/ab99c0.

[30] Qiao Wang, Weiguo Song, Jun Zhang, Liping Lian, and Siuming Lo. "Experimental study on single-file movement with different stop distances". In: *The Proceedings of 11th Asia-Oceania Symposium on Fire Science and Technology 11th*. Springer. 2020, pp. 241–253. DOI: 10.1007/978-981-32-9139-3_19.

[31] Qiao Wang, Weiguo Song, Jun Zhang, Rui Ye, and Jian Ma. "Experimental study on knee and hand crawling evacuation for different age group students". In: *International Journal of Disaster Risk Reduction* 48 (2020), p. 101613. DOI: 10.1016/j.ijdrr.2020.101613.

[32] Zhijian Fu, Tao Li, Qiangqiang Deng, Andreas Schadschneider, Lin Luo, and Jian Ma. "Effect of turning curvature on the single-file dynamics of pedestrian flow: an experimental study". In: *Physica A: Statistical Mechanics and its Applications* 563 (2021), p. 125405. DOI: 10.1016/j.physa.2020.125405.

[33] Tuantuan Lu, Yongxiang Zhao, Peng Wu, and Pengfei Zhu. "Dynamic analysis of single-file pedestrian movement with maintaining social distancing in times of pandemic". In: *Journal of Statistical Mechanics: Theory and Experiment* 2021.9 (2021), p. 093402. DOI: 10.1088/1742-5468/ac1c01.

[34] Yi Ma, Eric Wai Ming Lee, Meng Shi, and Richard Kwok Kit Yuen. "Spontaneous synchronization of motion in pedestrian crowds of different densities". In: *Nature human behaviour* 5.4 (2021), pp. 447–457. DOI: 10.1038/s41562-020-00997-3.

[35] Jianyu Wang, Jian Ma, Peng Lin, Majid Sarvi, and Ruoyu Li. "Pedestrian single file movement on stairway: Investigating the impact of stair configuration on pedestrian ascent and descent fundamental diagram". In: *Safety science* 143 (2021), p. 105409. DOI: 10.1016/j.ssci.2021.105409.

[36] Rui Ye, Yiping Zeng, Guang Zeng, Zhongyi Huang, Xiaolian Li, Zhiming Fang, and Weiguo Song. "Pedestrian single-file movement on stairs under different motivations". In: *Physica A: Statistical Mechanics and its Applications* 571 (2021), p. 125849. DOI: 10.1016/j.physa.2021.125849.

[37] Liping Lian, Rui Ye, Long Xia, Weiguo Song, Jun Zhang, and Xiaolian Li. "Pedestrian dynamics in single-file merging flows". In: *Physica A: Statistical Mechanics and its Applications* 600 (2022), p. 127549. DOI: 10.1016/j.physa.2022.127549.

[38] Peter Thompson, Hossein Tavana, Cathy Goulding, Håkan Frantzich, Karen Boyce, Daniel Nilsson, Gabriel Larsson, Jesper Friholm, and Denise McGrath. "Experimental analyses of step extent and contact buffer in pedestrian dynamics". In: *Physica A: Statistical Mechanics and its Applications* 593 (2022), p. 126927. DOI: 10.1016/j.physa.2022.126927.

[39] Sarah Paetzke, Maik Boltes, and Armin Seyfried. "Influence of Gender Composition in Pedestrian Single-File Experiments". In: *Applied Sciences* 13.9 (2023), p. 5450. DOI: 10.3390/app13095450.

[40] Maoyu Li, Lizhong Yang, Ping Zhang, Nan Jiang, Xinmiao Jia, and Hanchen Yu. "Single-file movement experiments of male under the influence of rhythm". In: -. Vol. 84. AHFE Open Acces, 2023, pp. 318–328. DOI: 10.54941/ahfe1003618.

[41] Nashiru Mumuni Daniel Bilintoh, Jun Zhang, Rehmat Karim, and Warda Rafaqat. "Experimental study of the effects of culture and location on single-file fundamental diagrams". In: *Heliyon* 9.9 (2023). DOI: 10.1016/j.heliyon.2023.e19378.

[42] Alexander Backlund. "The definition of system". In: *Kybernetes* 29.4 (2000), pp. 444–451. DOI: 10.1108/03684920010322055.

[43] Hanyi Xiao, Qiao Wang, Jun Zhang, and Weiguo Song. "Experimental study on the single-file movement of mice". In: *Physica A: Statistical Mechanics and its Applications* 524 (2019), pp. 676–686. DOI: 10.1016/j.physa.2019.04.032.

[44] Qiao Wang, Weiguo Song, Shujie Wang, and Siuming Lo. "Single-file Movement of Ants Stressed by a High Temperature". In: *Collective Dynamics* 5 (2020), pp. 98–106. DOI: 10.17815/CD.2020.39.

[45] Andrea Portz and Armin Seyfried. "Analyzing stop-and-go waves by experiment and modeling". In: *Pedestrian and Evacuation Dynamics*. Springer, 2011, pp. 577–586. DOI: 10.1007/978-1-4419-9725-8_52.

[46] Jun Zhang, Wolfgang Mehner, Stefan Holl, Maik Boltes, Erik Andresen, Andreas Schadschneider, and Armin Seyfried. "Universal flow-density relation of single-file bicycle, pedestrian and car motion". In: *Physics Letters A* 378.44 (2014), pp. 3274–3277. DOI: 10.1016/j.physleta.2014.09.039.

[47] Rui Jiang, Mao-Bin Hu, Qing-Song Wu, and Wei-Guo Song. "Traffic dynamics of bicycle flow: experiment and modeling". In: *Transportation science* 51.3 (2017), pp. 998–1008. DOI: 10.1287/trsc.2016.0690.

[48] Yuki Sugiyama, Minoru Fukui, Macoto Kikuchi, Katsuya Hasebe, Akihiro Nakayama, Katsuhiro Nishinari, Shin-ichi Tadaki, and Satoshi Yukawa. "Traffic jams without bottlenecks—experimental evidence for the physical mechanism of the formation of a jam". In: *New journal of physics* 10.3 (2008), p. 033001. DOI: 10.1088/1367-2630/10/3/033001.

[49] Shin-ichi Tadaki, Macoto Kikuchi, Minoru Fukui, Akihiro Nakayama, Katsuhiro Nishinari, Akihiro Shibata, Yuki Sugiyama, Taturu Yosida, and Satoshi Yukawa. "Phase transition in traffic jam experiment on a circuit". In: *New Journal of Physics* 15.10 (2013), p. 103034. DOI: 10.1088/1367-2630/15/10/103034.

[50] R. E. Stern, S. Cui, M. L. Delle Monache, R. Bhadani, M. Bunting, M. Churchill, N. Hamilton, R. Haulcy, H. Pohlmann, F. Wu, B. Piccoli, B. Seibold, J. Sprinkle, and D. B. Work. "Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments". In: *Transportation Research Part C: Emerging Technologies* 89 (2018), pp. 205–221. DOI: 10.1016/j.trc.2018.02.005.

[51] Biagio Ciuffo, Konstantinos Mattas, Michail Makridis, Giovanni Albano, Aikaterini Anesiadou, Yinglong He, Szilárd Josvai, Dimitris Komnos, Marton Pataki, Sandor Vass, and Zsolt Szalay. "Requiem on the positive effects of commercial adaptive cruise control on motorway traffic and recommendations for future automated driving systems". In: *Transportation Research Part C: Emerging Technologies* 130 (2021), p. 103305. DOI: 10.1016/j.trc.2021.103305.

[52] Xintong Li, Hang Yu, Weiguo Song, and Jun Zhang. "Investigation of pedestrian speed in formation evacuating in two specific water depths". In: *Safety science* 169 (2024), p. 106333. DOI: 10.1016/j.ssci.2023.106333.

[53] BD Hankin and Richard A Wright. "Passenger flow in subways". In: *Journal of the Operational Research Society* 9.2 (1958), pp. 81–88. DOI: 10.1057/jors.1958.9.

[54] Asja Jelić, Cécile Appert-Rolland, Samuel Lemercier, and Julien Pettré. "Properties of pedestrians walking in line. II. Stepping behavior". In: *Physical Review E* 86.4 (2012), p. 046111. DOI: 10.1103/PhysRevE.86.046111.

[55] Cheng-Jie Jin, Rui Jiang, and Da-Wei Li. "Influence of bottleneck on single-file pedestrian flow: Findings from two experiments". In: *Chinese Physics B* 29.8 (2020), p. 088902. DOI: 10.1088/1674-1056/ab8da3.

[56] Rudina Subaih, Mohammed Maree, Mohcine Chraibi, Sami Awad, and Tareq Zanoon. "Experimental investigation on the alleged gender-differences in pedestrian dynamics: A study reveals no gender differences in pedestrian movement behavior". In: *IEEE access* 8 (2020), pp. 33748–33757. DOI: 10.1109/ACCESS.2020.2973917.

[57] Maik Boltes and Armin Seyfried. "Collecting pedestrian trajectories". In: *Neurocomputing* 100 (2013), pp. 127–133. DOI: 10.1016/j.neucom.2012.01.036.

[58] Armin Seyfried, Maik Boltes, Jens Kähler, Wolfram Klingsch, Andrea Portz, Tobias Rupprecht, Andreas Schadschneider, Bernhard Steffen, and Andreas Winkens. "Enhanced empirical data for the fundamental diagram and the flow through bottlenecks". In: *Pedestrian and evacuation dynamics 2008* (2010), pp. 145–156. DOI: 10.1007/978-3-642-04504-2_11.

[59] Jun Zhang, Wolfram Klingsch, Andreas Schadschneider, and Armin Seyfried. "Transitions in pedestrian fundamental diagrams of straight corridors and T-junctions". In: *Journal of Statistical Mechanics: Theory and Experiment* 2011.06 (2011), P06004. DOI: 10.1088/1742-5468/2011/06/P06004.

[60] Guang Zeng, Andreas Schadschneider, Jun Zhang, and Weiguo Song. "Experimental study on the influence of background music on pedestrian movement in high densities". In: *Collective Dynamics* 5 (2020). DOI: 10.17815/CD.2020.42.

[61] Guang Zeng, Jun Zhang, Rui Ye, Andreas Schadschneider, Shuchao Cao, Qiao Wang, and Weiguo Song. "Pedestrian dynamics in single-file movement under background music with different tempos". In: *Advances in Complex Systems* 24.06 (2021), p. 2150011. DOI: 10.1142/S0219525921500119.

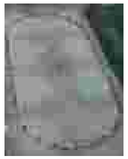
A Single-file Experiments

Table 3: Overview of the experimental publications reviewed by the authors that focus on single-file experiments for various traffic systems.

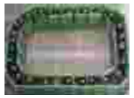
	Experiment (AuthorYear [cite])	Snapshot	Objects	Country/territory (where the experiment performed)	Environment	Setup shape/type	Main contribution *	Main result *
1	Seyfried2005 [1]		Pedestrians	Germany	Indoor	Oval	Investigate the velocity-density relation of unidirectional movement for pedestrians in different global densities	A linear relationship between the average velocities and the headway distances
2	Sugiyama2008 [48]		Cars (human-driven)	Japan	Outdoor	Circle	Experiment on the emergence of traffic jams in vehicle dynamics	Traffic jams emerge in a single-file system when vehicles move in a circle
3	Chattaraj2009 [2]		Pedestrians	India	Outdoor	Oval	Examine the impact of cultural factors and corridor length on the fundamental diagrams	The cultural factor influences the fundamental diagram, whereas the corridor length has no impact
4	Lukowski2009 [5]		Pedestrians	Germany	Indoor	Oval	Investigation of the influence of motivation (normal walking and walking under urgency) on pedestrian movement	Motivation affects pedestrian movement with different conditions leading to distinct fundamental diagrams

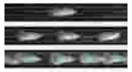
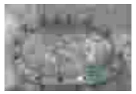
5	Liu2009 [6]		Pedestrians	China	Outdoor	Oval	Present and examine a pedestrian detection and tracking tool, along with a quantitative analysis of the microscopic characteristics of pedestrians	An automated tool using the mean-shift algorithm to extract head trajectories and quantify microscopic characteristics of pedestrians such as velocity, density, and lateral oscillation
6	Jezbera2010 [7]		Pedestrians	Czech Republic	Outdoor	Circle	Describe the statistical properties of headway distances using the Gaussian Unitary Ensemble of random matrices	Description of headway as derived from mathematical models of one-dimensional random walkers
7	Seyfried2010 [8, 58]		Pedestrians	Germany	Indoor	Oval	Analysis of pedestrian movement in congested situations	Coexistence of moving and stopping states as demonstrated by the velocity-density relationship
8	Yanagisawa2012 [9]		Pedestrians	Japan	Indoor	Circle	Propose a velocity model incorporating step size and walking pace	Rhythm improves flow in congested situations

9	Jelic2012 [10, 54]		Pedestrians	France	Indoor	Circle	Focus on the fundamental diagram (relationship between instantaneous velocity and headway distance)	The speed-headway exhibits a piecewise linear behavior in the large densities
10	Song2013 [11]		Pedestrians	China	Outdoor	Oval	Improve a one-dimensional continuous distance model by introducing desired direction and analyzing microscopic movement characteristics	The proposed model describes the one and two-dimensional movement
11	Tadaki2013 [49]		Cars (human-driven)	Japan	Indoor	Circle	Investigate how traffic jams can emerge even without bottlenecks at a certain high density	Jams occur at high densities, while free flow is maintained at low densities
12	Zhang2014 [46]		Bicycles	Germany	Outdoor	Oval	Identify a universal flow-density relationship for bicycle, pedestrian, and car movement systems	Despite different behaviors, the flow-density relationship is described by a universal fundamental diagram after rescaling
13	Cao2016 [12]		Pedestrians	China	Outdoor	Oval	Investigate movement characteristics across different age groups	Age composition influences velocity and the occurrence of stop-go waves

14	Ziemer2016 [13]		Pedestrians	Germany	Indoor	Oval	Analyze congestion dynamics using complete trajectory data (both straight and curved sections)	Describe the stop-and-go waves and fundamental diagrams, which have the same shape in both straight and curved sections of the setups
15	Zhao2017 [14]		Pedestrians, Bicycles	China	Outdoor	Circle	Compare and study the space-time trajectories and space-velocity diagrams of pedestrians, bicycles, and vehicle	Similarities exist between the space-time trajectories and space-velocity diagrams of traffic systems
16	Jiang2017 [47]		Bicycles	China	Outdoor	Oval	Study the characteristics of bicycle movement	Present the bicycle numbers-flow relation and analyze the spatiotemporal evolution of bicycle flow
17	Chen2017 [15]		Pedestrians	China	Indoor	Stairs	Investigate movement characteristics when ascending and descending stairs	Similar properties and different resolutions for density-speed and speed-headway diagrams are observed in ascending and descending movement

18	Ikeda2017 [16]		Pedestrians	Japan	Indoor	Circle	Show that a steady beat can enhance coordinated group walking and inter-subject neural synchrony in congested situations	A steady beat significantly improved walking flow and increased neural synchrony between individuals
19	Gulhare2018 [17]		Pedestrians	India	Outdoor	Oval	Compare data from a field study with controlled experiment	The data from experiments are different from the field data
20	Huang2018 [18]		Pedestrians	China	Indoor	Seat aisle	Investigate movement in narrow seat aisle	The speed of pedestrians changes with variations in aisle width
21	Ma2018 [19]		Pedestrians	China	Outdoor	Oval	Analysis of continuous stepping behaviors in interacting pedestrians	The relationship between step length and headway distance shows a piecewise linear behavior
22	Sun2018 [20]		Pedestrians	China	Indoor	Ship corridor	Investigate the effect of ship trim and heeling in movement characteristics	Trim angles impact pedestrians' speed more than heeling angles, which show less influence
23	Wang2018 [21]		Pedestrians	Germany	Indoor	Oval	Investigate the link between stepping and flow characteristics	There is a dependence between stepping locomotion and speed

24	Stern2018 [50]		Cars (autonomous vehicle)	USA	Outdoor	Circle	Reduce stop-and-go waves with intelligent control of autonomous vehicles	Reduce stop-and-go waves by controlling the velocity of a single vehicle in the system
25	Appert-Rolland2018 [22]		Pedestrians	France	Indoor	Circle (virtual, without predefined path), one-dimensional observation area	Examine how pedestrians adapt their trajectories in crowds	Pedestrians adjust their headway according to the leader's speed
26	Cao2019 [23]		Pedestrians	China	Outdoor	Rectangle with four straight corridors and four arcs	Understand the movement characteristics under limited visibility (light conditions)	Visibility conditions affect the occurrence of stop-and-go waves and the movement properties
27	Jin2019 [24, 55]		Pedestrian	China	Outdoor	Circle	Investigate movement characteristics in a high-density circular setup (4 pedestrians per square meter)	Quantitatively discuss the values of density and speed for the stop and moving states, as well as the critical density values
28	Ren2019 [25]		Pedestrian	China	Outdoor	Oval	Compare the movement characteristics of different age groups, with a focus on the elderly	The elderly stop for longer periods and walk more slowly than other age groups

29	Subaih2019 [26, 56]		Pedestrians	Palestine	Indoor	Oval	Investigate the influence of gender composition (male, female, mixed-random) on movement	Male and female groups walk at similar speeds, but they adjust their speed when moving together
30	Xiao2019 [43]		Mices	China	Indoor	One-dimensional observation area	Investigate the movement characteristics of mice	A decaying velocity-density relationship at low densities and a non-strict relationship at high densities
31	Huang2019 [27]		Pedestrians	China	Indoor	One-dimensional observation area	Analysis of movement characteristics for pedestrians carrying luggage	Luggage has a minor influence on individual speed but a significant impact on headway distances
32	Zeng2019 [28, 60, 61]		Pedestrians	China	Outdoor	Oval	Compare the movement characteristics with and without background music	With music there is a higher frequency of stop-and-go waves, longer headway distance and stopping durations
33	Ma2020 [29]		Pedestrians	China	Outdoor	Oval	Investigate movement characteristics under different height constraints	Height constraints affect movement characteristics

34	Wang2020 [44]		Ants	China	Indoor	One-dimensional observation area	Investigate ant movement under high-temperature stress	Random pauses and overtaking are observed among the ants
35	Wang2020a [30]		Pedestrians	China	Indoor	Rectangle	Investigate the impact of different stopping distances (normal, close) on movement	The type of stop influences the speed
36	Wang2020b [31]		Pedestrians	China	Outdoor	One-dimensional observation area	Investigate knee and hand crawling behavior during building evacuations in a fire scenario for different age groups	The speed of elementary school students is faster than that of college students
37	Fu2021 [32]		Pedestrians	China	Outdoor	Oval, circle	Study the effect of setup geometry (oval, circular) on movement characteristics	There is an influence of curvature on the flow properties
38	Lu2021 [33]		Pedestrians	China	Outdoor	Oval	Analysis movement characteristics while maintaining social distancing	Social distancing measures cause pedestrians to maintain greater distances compared to normal walking
39	Ma2021 [34]		Pedestrians	China	Outdoor	Oval	Study the synchronization of both legs in interacting pedestrians	Synchronization begins when the distance between pedestrians is too small for them to move forward

40	Wang2021 [35]		Pedestrians	China	Indoor	Stairs	Investigate the effect of stair configuration on pedestrian ascent and descent	The analysis shows a unified behavioral mechanism for pedestrian single-file movement on both horizontal planes and stairs
41	Ye2021 [36]		Pedestrians	China	Outdoor	Stairs	Analysis of pedestrian movement on stairs with different motivations (normal and fast walking)	In fast walking condition, pedestrians move at higher velocities compared to normal walking
42	Ciuffo2021 [51]		Cars (autonomous vehicle)	Hungary	Outdoor	Motorway with random shape	Evaluate the impact of adaptive cruise control systems on vehicle flow	Adaptive cruise control systems tend to increase traffic instability
43	Lian2022 [37]		Pedestrians	China	Outdoor	Branch	Investigate the merging flows of pedestrians at different angles	The speed-density relationship is not affected by the merging angle
44	Thompson2022 [38]		Pedestrians	Sweden	Indoor	Oval	Analyze the step extent and contact buffer of pedestrians while walking	Step extent and contact buffer are key parameters for determining interpersonal spacing
45	Paetzke2023 [39]		Pedestrians	Germany	Indoor	Oval	Compare the movement of pedestrians in gender-homogeneous and gender-heterogeneous groups	No effect of the gender of neighboring pedestrians on movement

46	Li2023 [40]		Pedestrians	China	Indoor	Square with four straight corridors and four arcs	Investigate the influence of rhythm on male pedestrian movement	Rhythm affects movement and increases the frequency of stop-and-go waves
47	Bilintoh2023 [41]		Pedestrians	African students living in China	Outdoor	Oval	Investigate the movement characteristics of pedestrians from the same country living in different locations	Location influences movement
48	Li2024 [52]		Pedestrians	China	Indoor	One-dimensional observation area	Investigate the speed of pedestrians walking in specific water depths	Speed increases as the water depth increases

* The main contribution and result reported as they appear in the original paper by the authors.

B Data Collection

Table 4: Overview of data collection from experiments on single-file pedestrian movement during ground-level evacuation scenarios with closed boundaries, as reviewed by the authors.

	Experiment (AuthorYear [cite])	Country/territory (where the experiment performed)	Surrounding environment	Setup shape/type	Data type	Data collection device	Data collection process
1	Seyfried2005 [1]	Germany	Indoor	Oval	Time instances	Digital camera (side-view, video recordings)	Semi-automatic
					Head trajectories	Stereo vision camera (bird's-eye view)	Automatic
2	Chattaraj2009 [2]	India	Outdoor	Oval	Time instances	Digital camera (side-view, video recordings)	Semi-automatic
3	Lukowski2009 [5]	Germany	Indoor	Oval	Time instances	Digital camera (side-view, video recordings)	Semi-automatic
					Head trajectories		
4	Liu2009 [6]	China	Outdoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recording)	Automatic
5	Jezbera2010 [7]	Czech Republic	Outdoor	Circle	Time instances	Light gate	Automatic

6	Seyfried2010 [8, 58]	Germany	Indoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recording)	Automatic
7	Yanagisawa2012 [9]	Japan	Indoor	Circle	Time instances	No details	No details
8	Jelic2012 [10, 54]	France	Indoor	Circle	Head and shoulders trajectories	Infrared camera (VICON motion capture system)	Automatic
9	Song2013 [11]	China	Outdoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recording)	Automatic
10	Cao2016 [12]	China	Outdoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recording)	Automatic
11	Ziemer2016 [13]	Germany	Indoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recording)	Automatic
12	Zhao2017 [14]	China	Outdoor	Circle	Head trajectories	Digital camera (bird's-eye view, video recording)	Automatic
13	Ikeda2017 [16]	Japan	Indoor	Circle	Frontopolar/ brain activity signals	NIRS	Automatic

					Number of pedestrians	Digital camera (side-view around the circle, video recording)	Semi-automatic
14	Gulhare2018 [17]	India	Outdoor	Oval	Time instances	Digital camera (side-view, video recordings)	Semi-automatic
15	Ma2018 [19]	China	Outdoor	Oval	Head and foot trajectories	Digital camera (bird's-eye view, video recordings)	Automatic (mean-shift algorithm)
16	Wang2018 [21]	Germany	Indoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic
17	Appert-Rolland2018 [22]	France	Indoor	Circle (virtual, without predefined path)	Head trajectories	Infrared camera (VICON motion capture system)	Automatic
18	Cao2019 [23]	China	Outdoor	Rectangle with four straight corridors and four arcs	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic
19	Jin2019 [24, 55]	China	Outdoor	Circle	Head trajectories	UAV drone camera (bird's-eye view, video recordings)	Automatic
20	Ren2019 [25]	China	Outdoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic

21	Subaih2019 [26, 56]	Palestine	Indoor	Oval	Head trajectories	Digital camera (side-view, video recordings)	Semi-automatic
22	Zeng2019 [28, 60, 61]	China	Outdoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic
23	Ma2020 [29]	China	Outdoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic
24	Wang2020a [30]	China	Indoor	Rectangle	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic
25	Fu2021 [32]	China	Outdoor	Oval, circle	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic
26	Lu2021 [33]	China	Outdoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic
27	Ma2021 [34]	China	Outdoor	Oval	Head and foot trajectories	Camcorders	Automatic
28	Lian2022 [37]	China	Outdoor	Branch	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic

29	Thompson2022 [38]	Sweden	Indoor	Oval	Right shoulder, hip, knee, the tip of the toe, and heel trajectories	Digital camera (side-view, video recordings)	Automatic
30	Paetzke2023 [39]	Germany	Indoor	Oval	Head trajectories	Digital camera (bird's-eye view, video recordings)	Automatic
31	Li2023 [40]	China	Indoor	Square with four straight corridors and four arcs	Head trajectories	UWB	Automatic
					No details	DJI camera (side-view, video recordings, entire setup)	No details
32	Bilintoh2023 [41]	African students living in China	Outdoor	Oval	Time instances	Digital camera (bird's-eye view, video recordings)	Semi-automatic

C Collected experimental data for testing the proposed analysis tool

Table 5: The details of the experiments, which are used to test our proposed analysis tool, comprise 28 datasets.

	Experiment (AuthorYear [cite])	Dimensions of the experimental setup					Radius [m]	Trajectory extraction	Camera top/side view	Frame-rate (fps)
		Investigates	Setup Central circumference [m]	Straight part length [m]	Measurement area length [m])	Corridor width (straight, curved) [m]				
1	Lukowski2009 [5]	Motivation - haste	17.30	4	2	0.8, 1.2	2.20	Manually	Side view	25
2	Seyfried2010 [58]	Stop-and-go waves	26.80	4	4	0.7, 0.7	3.00	PeTrack	Top view	25
3	Cao2016 [12]	Age	25.70	5	-	0.8, 0.8	2.90	PeTrack	Top view	25
4	Ziemer2016 [13]	Congestion Dynamics	26.84	4	-	1.0, 1.0	3.00	PeTrack	Top view	16
5	Wang2018 [21]	Step style	16.6	2.5	-	0.8, 0.8	2.25	PeTrack	Top view	25
6	Subaih2019 [26]	Gender	17.27	3.14	3.14	0.6, 0.6	2.05	PeTrack	Side view	25
7	Ren2019 [25]	Age	25.70	5	-	0.8, 0.8	2.50	PeTrack	Side view	25
8	Zeng2019 [28]	Motivation - music	21.93	5	-	0.8, 0.8	1.90	PeTrack	Top view	25
9	Ma2020 [29]	Height constraints	28.08	4	3	0.8, 0.8	2.4	PeTrack	Top view	25
10	Paetzke2023 [39]	Gender	14.97	2.3	-	0.8, 0.8	1.65	PeTrack	Top view	25

PUBLICATION II

Questioning the Anisotropy of Pedestrian Dynamics: An Empirical Analysis with Artificial Neural Networks

This article has been published by Subaih, R., Maree, M., Tordeux, A., and Chraibi, M. (2022). Questioning the anisotropy of pedestrian dynamics: An empirical analysis with artificial neural networks. Applied Sciences, 12(15), 7563. DOI: `https://doi.org/10.3390/app12157563`.

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Questioning the Anisotropy of Pedestrian Dynamics: An Empirical Analysis with Artificial Neural Networks

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Abstract

Identifying the factors that control the dynamics of pedestrians is a crucial step towards modeling and building various pedestrian-oriented simulation systems. In this article, we empirically explore the influential factors that control the single-file movement of pedestrians and their impact. Our goal in this context is to apply feed-forward neural networks to predict and understand the individual speeds for different densities of pedestrians. With artificial neural networks, we can approximate the fitting function that describes pedestrians' movement without having modeling bias. Our analysis is focused on the distances and range of interactions across neighboring pedestrians. As indicated by previous researches, we find that the speed of pedestrians depends on the distance to the predecessor. Yet, in contrast to classical purely anisotropic approaches - that are based on vision fields and assume that the interaction mainly depends on the distance in front - our results demonstrate that the distance to the follower also significantly influences the movement. Using the distance to the follower combined with the subject pedestrian's headway distance to predict the speed improves the estimation by 18% compared to the prediction using the space in front alone.

Keywords: Artificial Neural Networks, Pedestrian Dynamics, Distance Headway, Single-file movement, Interaction Range, Modeling

1 Introduction

For the sake of safe mass events, comfortable and efficient transport infrastructures, for example airports, many works are dedicated to understanding the laws governing crowd dynamics. In the last years, the number of empirical studies increased significantly, which led to gaining more insights into the movement of people. Additionally, these insights often offer useful criteria that validate models and evaluate the simulacrum of reality they create.

Trustworthy models are valuable tools that shed lights on unknown aspects of crowds and allow assessing and investigating new design and planning measures. However, most known modeling approaches make implicit assumptions on the way people move and interact with their environment. Cellular automata, for instance, assume that a pedestrians' motile behavior is determined by chemotaxis [1]. Another popular modeling Ansatz describes the crowd by differential equations; assuming constructed functions such as algebraic [2] or exponential [3] Newtonian forces that compactly describe the systems' evolution. It is worth to mention that in [4] the interaction energy between pedestrians was measured from field observations and not assumed.

Based solely on experimental evidence, in this work, we isolate the factors that influence the interactions between pedestrians in single-file movement. Contrary to the usual synergy between experimental and numerical investigations of pedestrian dynamics, where the former validates the latter, we try, through neural networks, to "extract" from empirical data the most relevant dependencies that determine the movement of pedestrians. Furthermore, classical pedestrian interaction models are anisotropic, assuming that people in front influence the dynamics more than people behind. For instance, most force-based models include vision field mechanisms affecting a weight depending on the bearing angle in the motion direction [2, 3, 5, 6]. This hypothesis, despite the reasonable limits of human perception and notions of fields of vision, is in most cases assumed a priori without statistical evidence. In this article, we analyze the interaction range in the single-file movement, including isotropic symmetric interaction models based on the distance to pedestrians behind as well. Recently, Artificial Neural Networks have been used successfully to estimate the speed of pedestrians in different complex geometries [7]. They allow identifying (with no modeling bias) which variables are relevant to the pedestrian by analyzing prediction errors. In this context, We investigate several factors influencing the dynamics, namely the interaction range with pedestrians in front and behind, and the isotropic nature of the pedestrian dynamics. Hereby, we focus our analysis on the influence of the distance to the follower, predecessor, and second predecessor pedestrian on the prediction of the subject pedestrian speed.

The rest of this article is organized as follows. In Section 2, we review and discuss several approaches proposed by researchers to predict pedestrians' movement characteristics using different methods and techniques. Then, in Section 3, the single-file movement experimental dataset is introduced and the data pre-processing methodology is described. Section 4 presents the structure of the artificial neural networks applied to investigate pedestrians' movement influential factors to predict future speeds. In Section 5 the speed prediction results using different input features are discussed. Finally, we summarize the article, make conclusions, and propose future works in Section 6.

2 Related Work

Recently, more attention has been given to studying the influential factors that control the dynamics of pedestrians in closed and open environments [8–13]. Understanding such factors can help in modeling complex pedestrians' movement. When dealing with complex systems, such as pedestrian dynamics, scientists generate numerous models based on different approaches, variables, and parameters [14]. For instance, force-based models (see [15] for a review) assume that pedestrians' deviation from their intended trajectories can be explained by external forces. Another Ansatz by Karamouzas et al. [4] follows a statistical-mechanical approach to measure the interaction energy between pedestrians based on the time to a potential future collision (time-to-collision). Tordeux et al. [16] introduce the walking time-gap as a parameter to model the pedestrian's movement. Van den Berg et al. [17] propose a model based on optimal collision-avoidance techniques to describe the movement of pedestrians in two-dimensional space. Another model, the Linear Trajectory Avoidance (LTA) model, introduced by Pellegrini et al. [18] takes into account both simple scene information in the form of destinations or desired directions and interactions between different pedestrians. Cellular Automaton model proposed by Schadschneider et al. [1] is inspired by the chemotaxis process, which ants use for communication. This discrete on-space model assumes that pedestrian transition to neighbor cell probability varies dynamically and is not constant. Thus, this model modifies the transition probabilities by considering the nearest-neighbor interactions to determine pedestrian's transition to the next state. The aforementioned classical models are anisotropic, i.e. they assume that pedestrians interact with people in their vision field, and this interaction is reduced with the people behind. For instance, most force-based models include a vision field affecting a weight depending on the bearing angle θ_{ij} [2, 3, 5, 6]. In the centrifugal and generalized centrifugal force model [2, 6], the weight is

$$\omega_1(\theta_{ij}) = \begin{cases} \cos(\theta_{ij}) & \text{if } |\theta_{ij}| < \pi/2 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

In the original social force model [3], the weight is

$$\omega_2(\theta_{ij}) = \begin{cases} 1 & \text{if } |\theta_{ij}| < \varphi \\ c & \text{otherwise} \end{cases} \tag{2}$$

where φ is the angle of sight while $0 < c < 1$ is a reduced perception factor. Extended social force models use the weight [5]

$$\omega_3(\theta_{ij}) = \lambda_i + (1 - \lambda_i)\frac{1 + \cos(\theta_{ij})}{2}, \ \ \lambda_i \approx 0.75 \tag{3}$$

Such mechanisms make the motion behavior highly anisotropic. For single-file motion, it may even induce the interaction model strictly anisotropic (i.e., depending solely on the distances in front). In this article, we analyze the interaction range in the single-file movement, including isotropic symmetric interaction models based on the distance to pedestrians behind as well. Furthermore, all previously discussed models introduce equations that provide a template for a large but tightly linked family of models. However, sometimes the choice of certain qualitative functions remains not justified, nor is it backed by empirical knowledge of pedestrian dynamics. Moreover, classical models have a bias that emerges from their form, which has restricted degrees of freedom. That means each model can be controlled by a few specific parameters inherent to the form of the model. The prediction quality usually depends on the pertinence of the model's form defined to describe pedestrians' movements.

Recently, many researchers proposed human trajectory prediction algorithms [19] arguing that neural networks have high flexibility and are devoid of any modeling bias. For example, Alahi et al. [13] develop the Social LSTM (S-LSTM) algorithm to predict the future trajectories of pedestrians depending on their past positions and the interactions with their neighbors. To model the social interaction, Alahi uses a social-pooling layer to allow sharing each neighboring pedestrians' LSTM hidden state to predict subject pedestrian's future positions. Alahi et al. algorithm improved the prediction of the next position approximately by a factor of 21% compared to the force-based model (SF) [3]. Xue et al. [20] develop a trajectory-prediction algorithm, called the Bi-prediction algorithm, based on the S-LSTM considering the importance of pedestrians' intended destinations in predicting their future trajectories. This two-stage prediction model employs bidirectional LSTM architecture to forecast multiple possible trajectories with different probabilities in the scene. In another research [21], the authors propose the MX-LSTM model, which adds to the previous models a new variable (direction of the pedestrian head) to improve the trajectory predictions (the model improves the prediction by approximately 19% compared to the SF classical model). All the aforementioned data-based approaches have been used to describe low-density situations using specific datasets (UCY [22], ETH [18], etc.) where social interactions techniques for collision avoidance take up to several meters.

Other researchers have focused on developing algorithms based on artificial neural networks to predict a pedestrian's speed. For instance, the study proposed by Tordeux et al. [7] applies feed-forward neural networks (FFNN) to predict the speed of pedestrians walking on different types of facilities (corridors and bottlenecks). Several FFNNs are presented to approximate the fitting function with different combinations of input features (relative positions, relative velocities, and mean distance to the nearest ten neighbors in front), hidden layers, and hidden neurons. The results of FFNN show improvement by 20% compared to the classical approach (Weidmann fitting model [23]) evaluated with mixed data (corridor and bottleneck). Another research by Tkachuk et al. [24]. The authors develop a system that simulates pedestrians' behavior during the evacuation process. The proposed system uses FFNN to predict how people act during evacuations. The acceleration and average velocity are used to predict each pedestrian's horizontal and vertical speeds. Another research by Yi Ma et al. [25] proposes an approach based on a multilayer perceptron artificial neural network for simulating pedestrians' behavior. The authors train the artificial neural network using pedestrians' actual movement data to encapsulate and predict their future behaviors. To verify the correctness of the proposed simulation system, the authors compared the simulation results of pedestrian counter-flow in a road-crossing situation and pedestrian collision avoidance with the actual experiments. The simulation results in both studies show that the proposed models based on artificial neural networks provide greater prediction accuracy by learning from actual experimental data rather than other models.

For brevity's sake, our focus in this article is to apply a FFNN to investigate and analyze empirically the impact of distance interaction range on dynamics of pedestrians without modeling bias. Unlike most current research works, we aim to analyze single-file movement in different homogeneous and heterogeneous gender flows to predict the pedestrian's speed.

3 Experimental Data and Measurement Methods

This section presents the empirical data to train and test the artificial neural networks. Furthermore, the measurement methods to calculate movement quantities (headway and speed) are described. To investigate pedestrians' speed, we used a dataset from experiments conducted in Palestine [12]. Single-file experiments were performed at the Arab American university in Palestine with a total of 47 participants (26 females and 21 males). Several experimental runs were performed focusing on the influence of gender factor on pedestrians' movement. Side view videos were captured using a digital camera for different numbers of pedestrians (densities) and various gender compositions. The experimental dataset includes the 1D trajectories recorded in different time frames and the gender information of each pedestrian (male and female). In the Palestine experiments, the data were obtained after performing several runs for pedestrians walking with the same gender composition (homogeneous: females alone, and males alone) or mixed (heterogeneous: male-female walking together)(see Figure 1). Our analysis will utilize the mixed-gender (UX, N=20, 24, 30), female (UF, N=20), and male (UM, N=20) experiments where N is the number of pedestrians in each run. In Figure 2 we see the trajectories of pedestrians in UX experiments over time. We can notice the emergence of stop-and-go waves for high densities (N=30) which means that the pedestrianise start to adjust their position to avoid collision.

Figure 1: Snapshots from Palestine experiments. Left: UM experiment, $N = 20$. Right: UX experiment, $N = 24$.

The same measurement method as [26] is used to calculate the individual speed and headway for pedestrians walking at each time frame. The speed of the pedestrian i is calculated at time t as follows:

$$v_i(t) = \frac{x_i(t + \Delta t/2) - x_i(t - \Delta t/2)}{\Delta t}, \qquad (4)$$

where Δt is a short time constant (10 frames, 0.4 sec.) and $x_i(t)$ is the x coordinate of pedestrian's i position at time t. We use the small value of $\Delta t = 0.4$ sec. to smooth the trajectories in order to avoid fluctuation of the pedestrian's step [27].

The headway is defined as the distance between a pedestrian i and its predecessor $i+1$:

$$h_i(t) = x_{i+1}(t) - x_i(t), \tag{5}$$

where x_{i+1} and x_i are the x coordinates of predecessor and subject pedestrian at time t, respectively.

These calculated movement quantities and associated pedestrian information are utilized as inputs to the FFNN. Table 1 demonstrate the descriptive statistics of the input and the output data we feed into the FFNNs. The first column of these tables presents the inputs (subject, predecessor, and follower pedestrian's headway distances) and the output (subject pedestrian speed).

Table 1: This table shows the descriptive statistics (number of pedestrians (N), mean, and standard deviation) for the Palestine dataset [26]. The second column contains the inputs and output that are used for the proposed FFNNs.

Experiment	Factor	No. of samples	Mean	SD	N
UX	Subject PD * speed (m/s)	15,893	0.219	0.111	15, 20, 24, 30
	Subject PD headway (m)		0.595	0.11	
	Predecessor PD headway (m)		0.608	0.124	
	Follower PD headway (m)		0.588	0.109	
UF	Subject PD speed (m/s)	422	0.615	0.102	20
	Subject PD headway (m)		0.711	0.104	
	Predecessor PD headway (m)		0.731	0.111	
	Follower PD headway (m)		0.712	0.120	
UM	Subject PD speed (m/s)	443	0.660	0.095	20
	Subject PD headway (m)		0.694	0.136	
	Predecessor PD headway (m)		0.689	0.121	
	Follower PD headway (m)		0.706	0.143	
UX	Subject PD speed (m/s)	435	0.500	0.104	20
	Subject PD headway (m)		0.717	0.119	
	Predecessor PD headway (m)		0.693	0.128	
	Follower PD headway (m)		0.704	0.126	

* PD is abbreviation for "pedestrian".

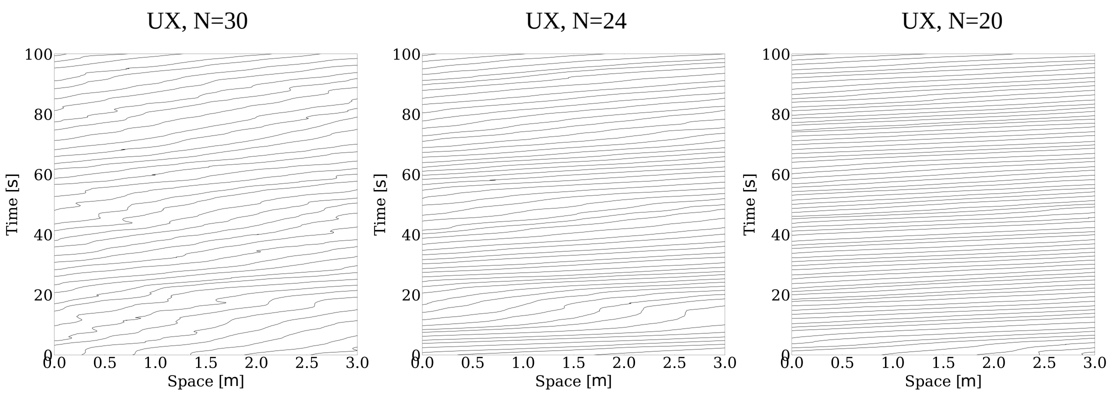

Figure 2: The trajectories over time for a sample data of UX experiments .

4 Structure of the Networks and Input Features

We apply several FFNNs to investigate the influence of interaction range (the distances with the neighbors) on pedestrian's speed. These networks are fed with various input features for training. We analyze the results using cross-validation to control eventual prediction overfitting and to determine the optimal complexity of the networks in terms of layer and neuron numbers [28]. In this technique, we resample the dataset by dividing the total dataset to 80% for training (i.e. UX experiments: 12,715 observations) and 20% for testing (i.e. UX experiments: 3178 observations) randomly. Furthermore, multiple iterations are applied following the bootstrap resampling technique to evaluate the error estimate precision and, by way, be able to determine whether an error difference is statistically significant or not [29, 30] (see Figure 3). Randomly subsampling the training and testing datasets allows us to obtain a distribution of the errors instead of a punctual estimate. The estimation is finally performed using the average of bootstrap subsamples error while the precision of estimation is evaluated using the bootstrap confidence interval represented as a boxplot. To quantify the error between the predicted and real values of the speed, we use the mean squared error (MSE) loss function:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2, \tag{6}$$

where n is the number of observations, Y is the vector of real speed values, and $\hat{Y}$ is the vector of predicted values.

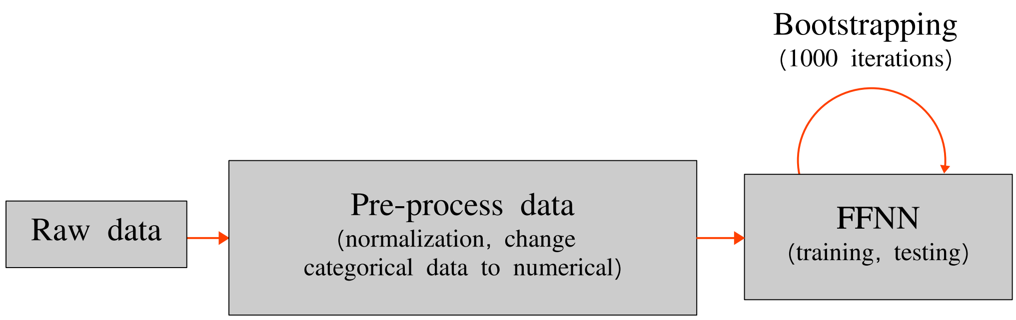

Figure 3: The methodology followed in developing the algorithms for speed prediction. In the pre-processing step, we change the categorical to numerical values and normalize the data between $[0, 1]$ to have the same scale of values (an important step before training for artificial neural networks).

The developed networks are trained using Adam optimizer [31] with a learning rate of $lr = 0.003$. During the training phase, the hyperparameters, namely the number of hidden layers and the number of hidden neurons, are tuned to reach a robust model. Also, the back-propagation algorithm [32] is used for training FFNNs by updating the weights' values. We fit the model using different epoch sizes and a batch size of 10, which in most cases is sufficient to verify the progress of learning. Moreover, the Sigmoid activation function is applied for all layers in the different versions of the developed algorithm. Finally, to build a prototype for the proposed prediction model, Keras framework [33] is utilized.

Different versions of the proposed FFNN are employed, varying in the number of input features fed into the input layer. These inputs indicate the movement characteristics of pedestrians walking in a single-file experimental setup. In the analysis, we focus on different combinations of the following headway distances as inputs:

1. Subject pedestrian headway (D).

2. Predecessor pedestrian headway (DP).

3. Follower pedestrian headway (DF).

Figure 4 illustrates the 1D path of single-file movement experiments, considering four pedestrians in the video frame. In the UX experiments, the people are distributed in an ordered manner (pedestrian i gender is male, female, male, etc.).

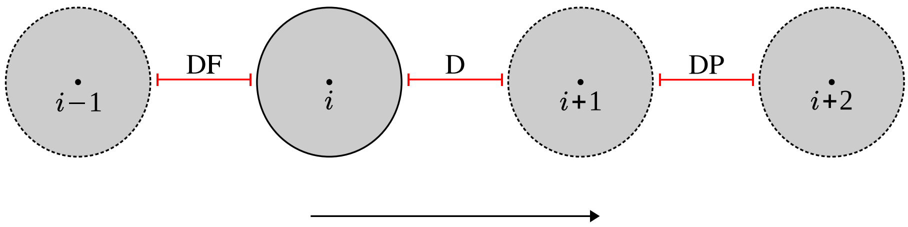

Figure 4: Illustration of pedestrians' positions in 1D scenario, indicating the investigated headway distances.

There is no standard approach for determining how many hidden layers and neurons should be used when building a prediction algorithm. Therefore, we follow Heaton's [34] approach, where it is recommended to set the number of the hidden layers to be between the number of input features and the number of outputs. We test several combinations of hidden layers and neurons ranged from neural networks with one hidden layer and one hidden neuron (i.e. shallow neural networks or logistics approach) to more complex networks with multiple layers and neurons (deep neural network). This makes the analysis global, starting from a basic statistical approach (a logistic regression) to complex networks, and allows the comparison of different modeling approaches. We tried several combinations of hidden layers and neurons (1), (2), (3), (3,2), (2,2), (32, 32), and (64) where (x) represents one hidden layer with x number of hidden neurons. Where (x,y) represents two hidden layers with a number x of hidden neurons in the first layer and number y of neurons in the second hidden layer. The prediction results show that the FFNN structure with two hidden layers (3, 2) (the first and second layers with three and two perceptrons, respectively)(see Fig. 5) is enough for speed prediction with our dataset.

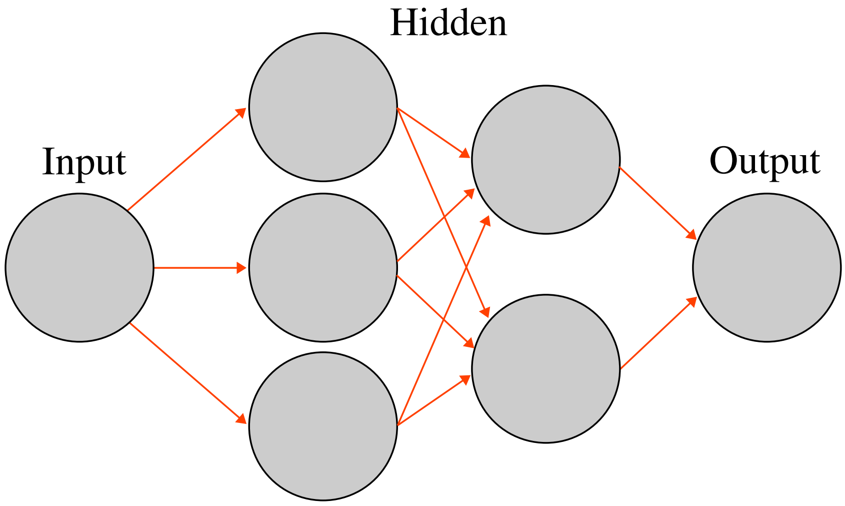

Figure 5: The structure of the feed forward neural network with two hidden layers (3, 2).

5 Results and Analysis

Our research aims to investigate the influence of the follower, predecessor, and second predecessor pedestrians' headway distances on the speed behavior of a pedestrian. The investigation examines the isotropic nature of the interaction behavior, considering that a pedestrian interact not only with pedestrians in their field of vision to regulate the speed but also with the pedestrians behind. We start training and testing several FFNNs with the Palestine dataset. To estimate the importance of different input features (DF, D, DP) on predicting the speed of pedestrians, we first feed each distance alone to the FFNN and then a combination of features. Seven networks with different input features are developed and validated:

1. In the networks DF, D, DP we have one input feature for each network: the headway distance of the follower pedestrian, subject pedestrian, and the predecessor pedestrian, respectively.
2. In networks $(DF + D)$, $(DF + DP)$, and $(D + DP)$ we predict the speed as a function of combinations of distances in front and behind to investigate the anisotropy of the pedestrians' interaction behavior.
3. The (*all*) network fed with the headway distances of the subject pedestrian and neighbors altogether $(DF + D + DP)$.

In Figure 6 the MSE values of the algorithms are visualized for training and testing phases using UX experiments, N=20, 24, 30 samples. As we can see, the gap between the training and testing MSE results is not wide. That means the algorithms are reliable, and there are no overfitting problems. It is also observed that the speed prediction is enhanced with increasing input features. Figure 7 shows the relative MSEs of the algorithms taking D-input network for comparison. We predict the individual speed by training the networks for several iterations following the bootstrap approach. Considering the impact of the influential factors, we compare the networks with the same number of inputs together. In networks with one input feature, the D improves the estimation of speed by 1.5% compared to DF algorithm. That means the distance with pedestrian in front has a higher impact on the speed prediction than the distance with the follower pedestrian. This result was confirmed previously as the headway distance is the main dependency in many models [35]. Moreover, the algorithm with DP increased the MSE by 13% compared to D algorithm. This result indicates that the headway distance of the second predecessor has no significant influence on the subject pedestrian's speed. In the case of two input factors, the algorithm $(DF + D)$ improves the performance of speed prediction by 16% and 11% in comparison with $(DF+DP)$ and $(D+DP)$ networks, respectively. Interestingly, the combination of distance with the pedestrian in front and right behind improves the speed prediction compared to the combination of headway distances in front. From observing experiments' videos, we notice that the pedestrians in relatively high densities start to adjust their speed when they approach the nearest neighbors to avoid colliding. This result demonstrates that the interaction behavior is not strictly anisotropic in single-file movement, contrary to classical modeling approaches assuming that the front distances only influence the speed. Therefore, it is suggested that a dynamical model that considers both distances D and DF is likely to describe more aspects of the single-file dynamics. Finally, the (all) algorithm which was fed with all headway distances as inputs improves the results by 21% compared to D algorithm (3% compared to the $(DF+D)$ algorithm). This result indicates that with many input features, we can improve the speed estimation with percent corresponding to the impact of the inputs.

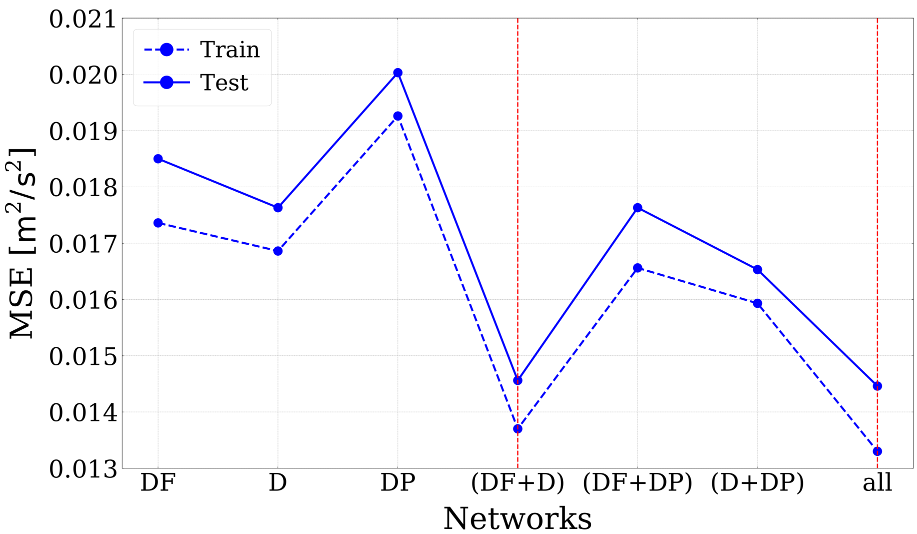

Figure 6: Visualization of the training and testing MSE values (using UX, N=20, 24, 30 samples) according to different input variables for networks with two hidden layers, including three and two hidden perceptrons, respectively. The red dashed line corresponds to the networks with the lowest values of MSEs.

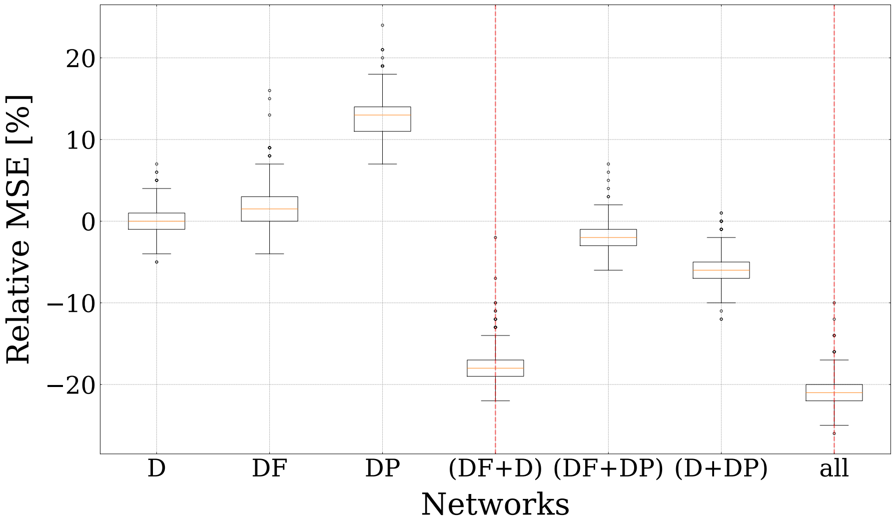

Figure 7: Boxplots represent the training MSE results of the algorithms using UX, N=20, 24, 30 samples with complexity (3,2). The X-axis represents the algorithm inputs we applied, and the y-axis denotes the relative MSE calculated with *D*-input algorithms as a reference case.

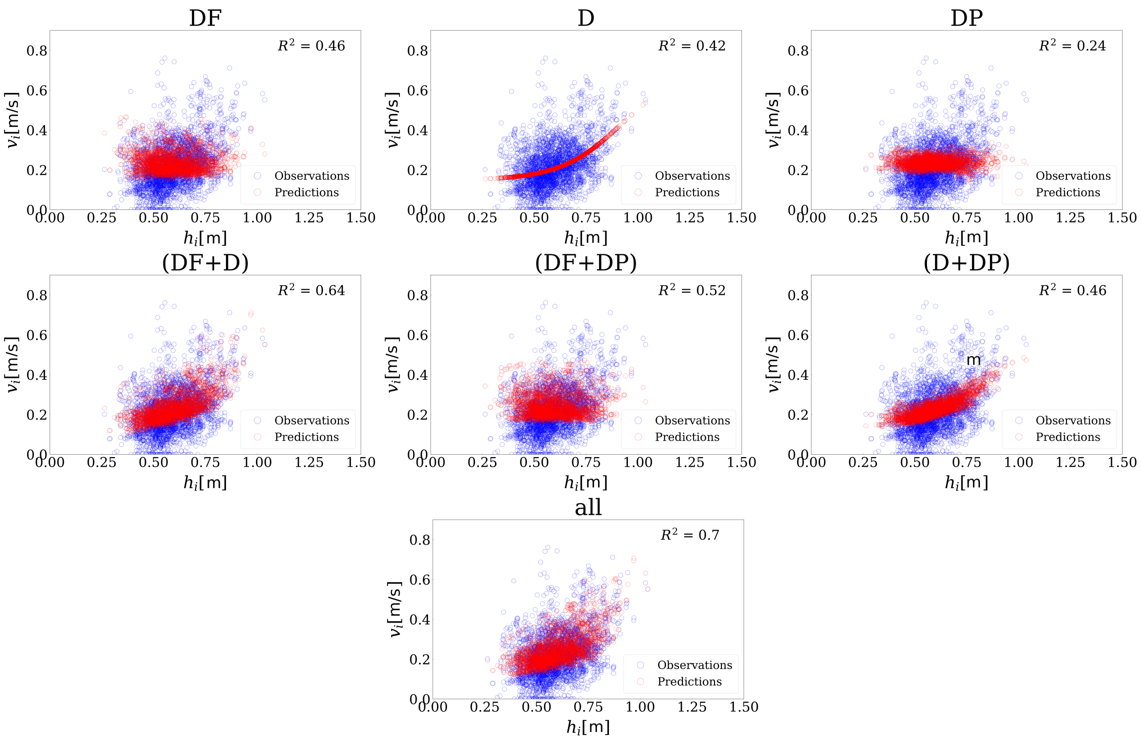

Figure 8: Examples of speed predictions from testing the neural networks (D, DF, (DF+D), (DF+DP), (DP+D), all) using UX, N=20, 24, 30 samples. As observed in the actual data (in blue), the speed values for given headway distances tend to be close to the observed values when we combine DF and D as inputs to the FFNN algorithm or when we have more input features (*all*). R^2 values on the top-right of the figure are calculated to compare the variability of the estimated speed.

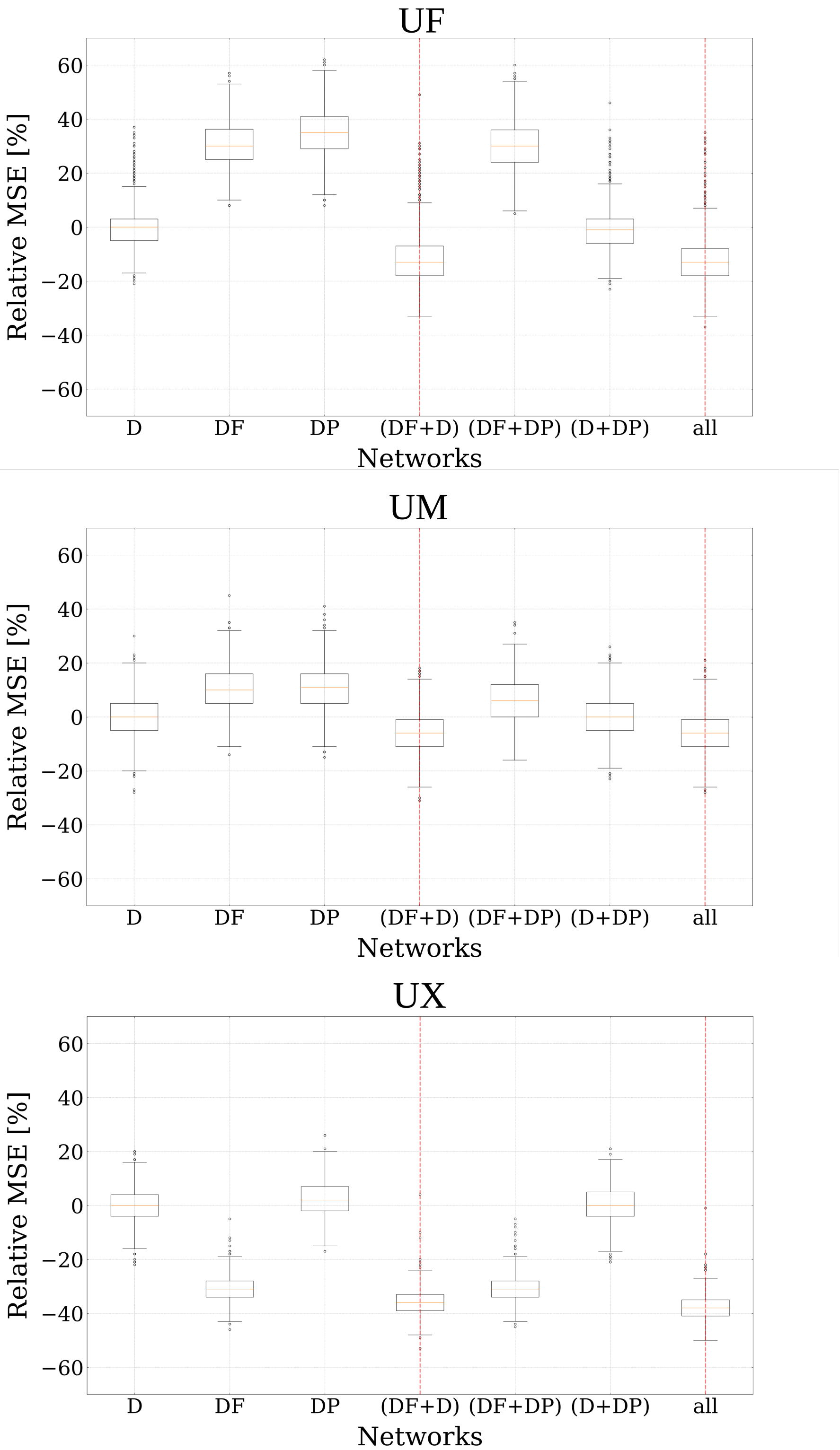

Figure 9: Boxplots represent the training MSE results of the algorithms with complexity (3,2) using UF, UM, UX, and N=20 samples. The X-axis represents the algorithm inputs we applied, and the y-axis denotes the relative MSE calculated with *D*-input algorithms as a reference case.

Figure 8 visualizes the relationship between the subject pedestrian headway distances and the speed values (actual and predicted) for different networks fed with UX, N=20, 24, 30 data samples. The networks with the higher number of inputs can recapture the variability of the data points. As shown in the sub-figures, the algorithms with the optimal speed prediction results (best input combinations) have the highest R^2 values ($(DF + D)$ and (all)). In other words, the optimal algorithms capture the data points' variability better than algorithms with inputs of low impact on the speed.

To investigate the influence of the different distances in front and behind in heterogeneous and homogenous gender groups, we trained the same FFNN structure with data for experiments UF, UM, and UX with N=20 pedestrians. As shown in Figure 9 the distance to the pedestrian behind significantly improves the speed prediction compared to the distance in front for experiments UF, UM, and UX as well. For the UX experiments (N=20), the improvement provided by the distance behind is significant 36% compared to D algorithm (see Figure 9, UX). It is less for the experiment UF and UM composed of solely female (14%) and males (7%). Furthermore, the small sizes of the samples do to not allow to systematically demonstrate statistically that the differences are significant since the boxplots partly overlap. Nevertheless, the influence of the distance behind is observed for flow solely composed of males and females, especially for the females. It is, however, clearly more pronounced for the mixed gender flow. Therefore, it is not to exclude that gender effects in the mixed flow alternating male and female reinforce the influence of the pedestrian behind. Further empirical analysis with more data samples should emphasize the influence of distance behind on the pedestrian's speed for homogeneous or random mixed gender groups.

6 Conclusion

This article investigates the impact of headway distances and the interaction range on pedestrian's movement by the mean of FFNN. Previous research generally assumes that the pedestrians' movement is mostly influenced by people in their field of vision, i.e., in the direction of motion. Such question rely on the anisotropic nature of the pedestrian interaction behavior. In our research, we analyze the influence of the range of interaction with the distances behind and in front on pedestrian's speed in single-file movement experiments. We predict the speed of pedestrians using a single-file experimental dataset performed in Palestine including uniformly mixed and homogeneous gender flow. Because relatively simple mechanisms primarily govern single-file movement, our investigation reveals that a shallow feedforward neural network structure (3, 2) is sufficient to fit the data optimally.

We explore several algorithms by changing the number and type of input distance features. The findings show that a prediction algorithm including the distance to the follower pedestrian as the input feature improves the MSE results by a factor up to 18% compared to an algorithm solely based on the distance in front. Such improved may reach up to 36% for certain experiments. Whereas, taking into account the headway distance of the second predecessor has no strong influence on subject pedestrian's speed. Even if they are still significantly observed for gender homogeneous flow, such features are especially pronouced for uniform mixed gender experiments. Therefore, it is not to exclude that the influence on the motion of the pedestrian behind is reinforced by gender effects.

Many previous research assumes that the pedestrian motion is strongly anisotropic, i.e., mostly influenced by the environment in the motion direction. However, we observe that the distance behind in single-file motion plays a role in the dynamic. These results suggest that the follower headway (DF) is a potential influential factor that significantly improves the prediction of pedestrian speed. It might be considered a modeling input. Yet the correlation we observe may be the consequence of an anisotropic mechanism. Such an assumption should be tested using isotropic and anisotropic models.

For homogeneous gender groups (UF, and UM), we can notice that the distance behind the pedestrian influence the prediction of the speed. This is especially the case for the experiments with female. However, further empirical analysis with more data samples is needed to highlight this conclusion. For future work, we aim to experimentand generalise the anisotropy of pedestrian behavior for more complex and geometries and dynamics, and to take into account further factors beside gender, e.g., cultural and age effects.

Author Contributions: Conceptualization, M.M.; Formal analysis, R.S. and A.T.; Methodology, M.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the German Federal Ministry of Education and Research (BMBF: funding number 01DH16027) and the French National Research Agency (ANR) as well as the German Research Foundation (DFG), funding number 446168800.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Acknowledgments: This work was supported by the German Federal Ministry of Education and Research (BMBF: funding number 01DH16027) within the framework of the Palestinian–German Science Bridge project. MC and AT acknowledge the Franco–German research project MADRAS funded in France by the Agence Nationale de la Recherche (ANR, French National Research Agency), grant number ANR-20-CE92-0033, and in Germany by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation), grant number 446168800.

Conflicts of Interest: The authors declare that there is no conflict of interest regarding the publication of this paper.

References

[1] Andreas Schadschneider. "Cellular automaton approach to pedestrian dynamics-theory". In: *In: Schreckenberg M, Sharma SD (eds) Pedestrian and evacuation dynamics. Springer, Berlin/Heidelberg* (2001), pp. 75–86.

[2] Mohcine Chraibi, Armin Seyfried, and Andreas Schadschneider. "Generalized centrifugal-force model for pedestrian dynamics". In: *Physical Review E* 82.4 (2010), p. 046111.

[3] Dirk Helbing and Peter Molnar. "Social force model for pedestrian dynamics". In: *Physical review E* 51.5 (1995), p. 4282.

[4] Ioannis Karamouzas, Brian Skinner, and Stephen J Guy. "Universal power law governing pedestrian interactions". In: *Physical review letters* 113.23 (2014), p. 238701.

[5] Dirk Helbing, Lubos Buzna, Anders Johansson, and Torsten Werner. "Self-organized pedestrian crowd dynamics: Experiments, simulations, and design solutions". In: *Transportation science* 39.1 (2005), pp. 1–24.

[6] WJ Yu, R Chen, Li-Yu Dong, and SQ Dai. "Centrifugal force model for pedestrian dynamics". In: *Physical Review E* 72.2 (2005), p. 026112.

[7] Antoine Tordeux, Mohcine Chraibi, Armin Seyfried, and Andreas Schadschneider. "Prediction of pedestrian dynamics in complex architectures with artificial neural networks". In: *Journal of Intelligent Transportation Systems* (2019), pp. 1–13.

[8] Isabelle Maroger, Noelie Ramuzat, Olivier Stasse, and Bruno Watier. "Human Trajectory Prediction Model and its Coupling with a Walking Pattern Generator of a Humanoid Robot". In: *IEEE Robotics and Automation Letters* 6.4 (2021), pp. 6361–6369.

[9] Deepak Sharma, Amol P Bhondekar, AK Shukla, and C Ghanshyam. "A review on technological advancements in crowd management". In: *Journal of Ambient Intelligence and Humanized Computing* 9.3 (2018), pp. 485–495.

[10] Yingying Ma, Siyuan Lu, and Yuanyuan Zhang. "Analysis on Illegal Crossing Behavior of Pedestrians at Signalized Intersections Based on Bayesian Network". In: *Journal of Advanced Transportation* 2020 (2020).

[11] Flurin S Hänseler, Jeroen PA van den Heuvel, Oded Cats, Winnie Daamen, and Serge P Hoogendoorn. "A passenger-pedestrian model to assess platform and train usage from automated data". In: *Transportation Research Part A: Policy and Practice* 132 (2020), pp. 948–968.

[12] Rudina Subaih, Mohammed Maree, Mohcine Chraibi, Sami Awad, and Tareq Zanoon. "Gender-based Insights into the Fundamental Diagram of Pedestrian Dynamics". In: *International Conference on Computational Collective Intelligence*. Springer. 2019, pp. 613–624.

[13] Alexandre Alahi, Kratarth Goel, Vignesh Ramanathan, Alexandre Robicquet, Li Fei-Fei, and Silvio Savarese. “Social lstm: Human trajectory prediction in crowded spaces”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition.* 2016, pp. 961–971.

[14] Hairong Dong, Min Zhou, Qianling Wang, Xiaoxia Yang, and Fei-Yue Wang. “State-of-the-art pedestrian and evacuation dynamics”. In: *IEEE transactions on intelligent transportation systems* 21.5 (2019), pp. 1849–1866.

[15] Mohcine Chraibi, Antoine Tordeux, Andreas Schadschneider, and Armin Seyfried. “Modelling of pedestrian and evacuation dynamics”. In: *Encyclopedia of complexity and systems science* (2018), pp. 1–22.

[16] Antoine Tordeux, Mohcine Chraibi, and Armin Seyfried. “Collision-free speed model for pedestrian dynamics”. In: *Traffic and Granular Flow’15* (2016), pp. 225–232.

[17] Jur Van Den Berg, Stephen J Guy, Ming Lin, and Dinesh Manocha. “Reciprocal n-body collision avoidance”. In: *Robotics research* (2011), pp. 3–19.

[18] Stefano Pellegrini, Andreas Ess, Konrad Schindler, and Luc Van Gool. “You’ll never walk alone: Modeling social behavior for multi-target tracking”. In: *2009 IEEE 12th International Conference on Computer Vision.* IEEE. 2009, pp. 261–268.

[19] Andrey Rudenko, Luigi Palmieri, Michael Herman, Kris M Kitani, Dariu M Gavrila, and Kai O Arras. “Human motion trajectory prediction: A survey”. In: *The International Journal of Robotics Research* 39.8 (2020), pp. 895–935.

[20] Hao Xue, Du Q Huynh, and Mark Reynolds. “Bi-prediction: pedestrian trajectory prediction based on bidirectional LSTM classification”. In: *2017 International Conference on Digital Image Computing: Techniques and Applications (DICTA).* IEEE. 2017, pp. 1–8.

[21] Irtiza Hasan, Francesco Setti, Theodore Tsesmelis, Alessio Del Bue, Fabio Galasso, and Marco Cristani. “MX-LSTM: mixing tracklets and vislets to jointly forecast trajectories and head poses”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.* 2018, pp. 6067–6076.

[22] Alon Lerner, Yiorgos Chrysanthou, and Dani Lischinski. “Crowds by example”. In: *Computer graphics forum.* Vol. 26. Wiley Online Library. 2007, pp. 655–664.

[23] Ulrich Weidmann. “Transporttechnik der fußgänger: transporttechnische eigenschaften des fußgängerverkehrs, literaturauswertung”. In: *IVT Schriftenreihe* 90 (1993).

[24] Konstantin Tkachuk, Xiao Song, and Irina Maltseva. “Application of artificial neural networks for agent-based simulation of emergency evacuation from buildings for various purpose”. In: *IOP Conference Series: Materials Science and Engineering.* Vol. 365. IOP Publishing. 2018, p. 042064.

[25] Yi Ma, Eric Wai Ming Lee, and Richard Kwok Kit Yuen. “An artificial intelligence-based approach for simulating pedestrian movement”. In: *IEEE Transactions on Intelligent Transportation Systems* 17.11 (2016), pp. 3159–3170.

[26] Rudina Subaih, Mohammed Maree, Mohcine Chraibi, Sami Awad, and Tareq Zanoon. "Experimental Investigation on the Alleged Gender-differences in Pedestrian Dynamics: A Study Reveals No Gender Differences in Pedestrian Movement Behavior". In: *IEEE Access* 8 (2020), pp. 33748–33757. DOI: 10.1109/ACCESS.2020.2973917.

[27] Jiayue Wang, Wenguo Weng, Maik Boltes, Jun Zhang, Antoine Tordeux, and Verena Ziemer. "Step styles of pedestrians at different densities". In: *Journal of statistical mechanics: theory and experiment* 2018.2 (2018), p. 023406.

[28] Tom Dietterich. "Overfitting and undercomputing in machine learning". In: *ACM computing surveys (CSUR)* 27.3 (1995), pp. 326–327.

[29] Ron Kohavi et al. "A study of cross-validation and bootstrap for accuracy estimation and model selection". In: *Ijcai*. Vol. 14. Montreal, Canada. 1995, pp. 1137–1145.

[30] Thomas J DiCiccio and Bradley Efron. "Bootstrap confidence intervals". In: *Statistical science* 11.3 (1996), pp. 189–228.

[31] Diederik P Kingma and Jimmy Ba. "Adam: A method for stochastic optimization". In: *International Conference on Learning Representations (ICLR)* (2014).

[32] David E Rumelhart, Geoffrey E Hinton, and Ronald J Williams. "Learning representations by back-propagating errors". In: *nature* 323.6088 (1986), pp. 533–536.

[33] François Chollet et al. "Keras: The python deep learning library". In: *Astrophysics Source Code Library* (2018), ascl–1806.

[34] Jeff Heaton. *Introduction to neural networks with Java*. Heaton Research, Inc., 2008.

[35] Antoine Tordeux, Mohcine Chraibi, Andreas Schadschneider, and Armin Seyfried. "Influence of the number of predecessors in interaction within acceleration-based flow models". In: *Journal of Physics A: Mathematical and Theoretical* 50.34 (2017), p. 345102.

PUBLICATION III

Modeling pedestrian single-file movement: Extending the interaction to the follower

This article has been published by Subaih, R., and Tordeux, A. (2024). Modeling pedestrian single-file movement: Extending the interaction to the follower. Physica A: Statistical Mechanics and its Applications, 633, 129394. DOI: https://doi.org/10.1016/j.physa.2023.129394.

Author's Contributions

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Validation: Rudina Subaih, and Antoine Tordeux
Formal analysis: Rudina Subaih, and Antoine Tordeux
Visualization: Rudina Subaih
Data curation: Rudina Subaih
Writing – Original draft preparation: Rudina Subaih
Writing – Review and editing: Rudina Subaih, and Antoine Tordeux

Modeling pedestrian single-file movement: extending the interaction to the follower

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Abstract

This article proposes a new microscopic speed model for one-dimensional pedestrian movement. Most existing modeling approaches consider only the distance and relative speed between a pedestrian and the person in front resulting in totally asymmetric interaction models. However, the distance with the pedestrian behind may also influence the behavior of a pedestrian. Based on this assumption, we elaborate a new asymmetric microscopic model considering the relative distances with the nearest neighbors behind and ahead using a fine-tuning asymmetry parameter. We analyze the stability of the new model and calibrate the parameters using two different single-file movement datasets. The numerical simulation results show that the new model has fewer backward movements and pedestrian overlaps than the totally asymmetric model making the stop-and-go waves in crowded situations more realistic. Furthermore, the proposed fine-tuned model better describes the fundamental diagram and its scattering.

Keywords: Pedestrian dynamics, Single-file movement, Microscopic model, Least squares parameter estimate, Fundamental diagram, Stop-and-go waves

1 Introduction

Modeling pedestrian dynamics is essential to organizing safe and efficient crowded events. For instance, the models can be used to develop simulation software and assist in decision-making, risk management, and policy development for large pedestrian events. Various models have been developed to describe single-file pedestrian movements [1–7]. Generally speaking, pedestrian models are mainly categorized as microscopic [7–14] and macroscopic [15–20] based on the motion characteristics investigated (see [21] for review). Macroscopic models describe the aggregate characteristics of crowds, while microscopic models focus on the movement of individual pedestrians. Furthermore, the models can be discrete, such as microscopic cellular automata and macroscopic lattice models, or continuous, using systems of differential equations. The cellular automata models are random by nature, whereas in continuous approaches stochasticity can be introduced through adding noise to the dynamics. All these models are subject to many modeling assumptions that describe the way people move and interact with their environment. Several parameters and variables have been introduced in microscopic models to describe pedestrian interaction behaviors in single-file motions. In most cases, the models are totally asymmetric, i.e., the interaction model is only based on the distance to the nearest pedestrian in front and the speed of that pedestrian.

In this paper, we propose a new microscopic stochastic model to describe pedestrians' single-file movement. The originality of the approach lies in the interaction model, which also depends on the distance to the pedestrian behind. The model is inspired by previous statistical investigations [22] and empirical observations of coordination phenomena in single-file motion [23]. A parameter fine-tuning the relative distance to the neighbors in front and behind is applied. To study the model's behavior, we analyze the linear stability focusing on the role of the weight of the relative distances. We then calibrate the parameters of the deterministic speed model using two single-file movement datasets and different methods: statistically by least squares and empirically by simulation. Finally, we numerically investigate the movement of pedestrians in one-dimensional space and compare the simulation results with the totally asymmetric model and the real data. The simulation analysis focuses on space-time trajectories and fundamental diagrams (headway-speed relation). A summary of our methodology is presented in Figure 1. The results show that the new model improves the description of the fundamental diagram scattering and stop-and-go waves, making the simulation results more realistic.

The rest of the paper is structured as follows: we review and discuss the literature on pedestrian single-file movement models in Section 2. In Section 3, the microscopic speed model considering the symmetric interaction is defined. Then, in Section 4, we analyze the linear stability of the deterministic model to investigate theoretically the behavior of the proposed first-order speed model. The calibration of the model's parameters is presented in Section 5. In Section 6, the simulation results are presented and discussed. Finally, in Section 7, we summarize the content of the paper.

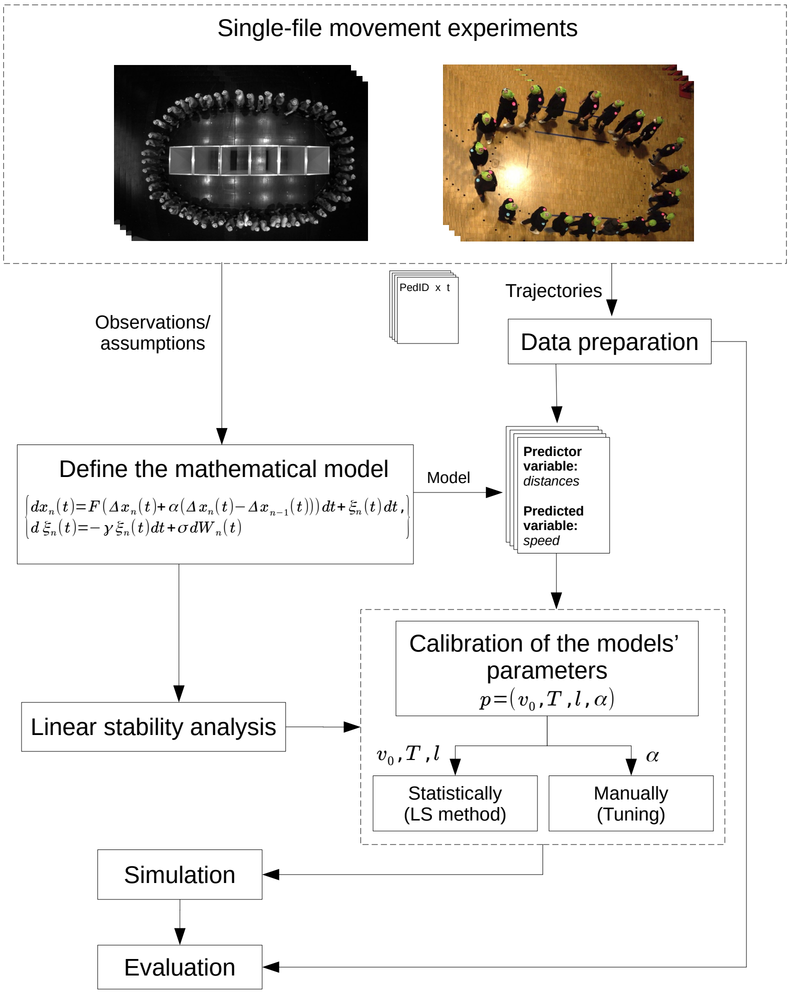

Figure 1: Key methodological milestones in the process of defining and evaluating the proposed pedestrian speed model.

2 Related Work

To better understand pedestrian dynamics in complex movement systems, many researchers investigate and model pedestrian behavior in one-dimensional space. Many single-file movement experiments (pedestrians walking in a single line or queue) have been performed to observe and analyze the factors that influence pedestrians' speeds, e.g., recent experiments performed in Germany, Palestine, and Japan [24–26]. Further pedestrian trajectories from single-file experiments are available online [1]. The single-file experiments provide a basic analysis of pedestrian dynamics, focusing on the fundamental relationship between speed and distance from neighbors. Various models based on the experiments have been developed in the literature to reproduce the observed trajectories as closely as possible. The observation of the experiments inspired, for instance, Chraibi et al. [7] to introduce the velocity-dependent volume

[1]Pedestrian dynamics data archive: https://ped.fz-juelich.de/da/doku.php

exclusion of pedestrians into the force-based model. The authors observed from the experiments that pedestrians' speed is influenced by their shoulder rotation while avoiding others, leading them to conclude that using a dynamic agent shape would be more effective than a static one. This results in the improvement of the simulation of pedestrians in crowds. Another study by Cordes et al. [1] applies the concept of time-to-collision (TTC) to model single-file pedestrian movement. The authors assume that the TTC quantifies the distance to a collision (between pedestrians) by combining spatial distances and velocities. That aims to give rise to a new class of models that represent the interactions among pedestrians by evolving TTC.

Several pedestrian models were proposed, drawing inspiration from other models. For instance, using car-following models to describe the single-file movement, Lemercier et al. [4] elaborated a pedestrian interaction model. The model focuses on the following behavior of pedestrians walking in corridors or queues. The authors verified the Aw et al. [27] road traffic model in pedestrian traffic and formulated a new model of interactions adapted to crowd simulation. Kuang et al. propose an extended optimal velocity model [5]. This model simulates the single-file movement in high density considering the interaction forces (repulsive and attractive forces) between pedestrians. Other pedestrian single-file models are derived from two-dimensional force-based models, such as [3, 6]. The issues of agent overlapping and oscillation in the social force model (as mentioned in [8, 28–31]) can be linked, in a one-dimensional case, to the limitations of the optimal velocity car-following model. To prevent backward movements, oscillations, and collisions, the optimal velocity (OV) model requires fine-tuning of the parameters [32]. Such unrealistic simulations' shortcomings of single-file behavior can be addressed using extended models.

The distance behind is introduced in considerable traffic system models (vehicle models) [33–38]. For example, Ge et al. [37] propose an extended car-following model by introducing the backward-looking effect. The model considers several vehicles ahead and one behind in a single lane. The simulation of the space-time evolution of the car headways shows that the model suppressed the traffic jam. Additionally, the findings of the linear stability analysis demonstrate that taking into account the backward-looking effect leads to the stabilization of the traffic system. Minghui Ma et al. [33] also propose an improved car-following model (cars driven in a single-file setup) by considering the backward-looking behavior and motion information of multiple vehicles. The drivers usually look behind while driving to avoid collisions with other vehicles. The simulation results show an efficient improvement in the avoidance of traffic congestion and enhance the stability of the traffic flow in comparison to the models that include only the distance in front. In pedestrian dynamics, Rio et al. [23] investigate the visual control of pedestrians following behavior. Using experimental investigations, the authors study how pedestrians adjust their walking speed when following a leader, based on the visual information provided by the leader's movements. The study involved experiments with pairs of participants walking in a straight line, with one person leading and the other following. The results show that the follower's walking speed is influenced by the leader's speed and visual cues, including the leader's head movements and changes in the walking direction. Considering the findings of Rio et al., we assume that there is coordination between the distances of pedestrians and their neighbors in the crowd, which influences the individual speeds of pedestrians.

In summary, existing pedestrian single-file movement models are systematically totally asymmetric and can encounter problems with overlapping and backward motion. Such difficulties are well-known for car-following models and can be overcome by extending the interaction to the agent behind [33, 39], leading to stability improvement and better collective coordination. Besides, collective coordination is observed in pedestrian single-file movements [23]. Furthermore, recent statistical analysis using feed-forward neural networks devoid of modeling bias shows that the distance behind improves the speed prediction [22]. These statements motivate us to extend a stochastic pedestrian single-file model by incorporating the distance to the pedestrian behind. Including the distance behind reduces unrealistic pedestrian overlaps and backward movements, which are observed in totally asymmetric models under high-density conditions. The model is a scaled-down version used to demonstrate specific aspects of the original system with fewer influential factors and in a simplified way.

3 Proposed Model

We consider a single-file movement of pedestrians in continuous time on a uni-dimensional space of length L with periodic boundary conditions. The pedestrians initially ordered by their indexes $n = 1, 2, \ldots, N$ and assume that the follower and predecessor of the n-th pedestrian are the $(n-1)$-th and $(n+1)$-th pedestrians at any time, respectively. Due to the periodic boundary conditions, the predecessor of the last pedestrian is the first agent and the follower of the first pedestrian is the last one as illustrated in Figure 2. The x-axis position of a pedestrian n at time t is denoted as $x_n(t)$. To calculate the distances between the consecutive pedestrians, we subtract the positions as:

$$\begin{cases} \Delta x_n(t) = x_{n+1}(t) - x_n(t), & n = 1, \ldots, N-1, \\ \Delta x_N(t) = L + x_1(t) - x_N(t). \end{cases} \tag{1}$$

In the proposed pedestrian single-file model, we assume that pedestrians can feel how close (the distance) the person behind is, which affects how they behave and extends the interaction. For the n-th pedestrian, the model is given by the following stochastic differential equation:

$$\begin{cases} dx_n(t) = F\big(\Delta x_n(t) + \alpha(\Delta x_n(t) - \Delta x_{n-1}(t))\big)dt + \xi_n(t)dt, \\ d\xi_n(t) = -\gamma \xi_n(t)dt + \sigma dW_n(t). \end{cases} \tag{2}$$

Here the speed of a pedestrian is an OV function F coupled to a stochastic noise provided by the Ornstein-Uhlenbeck process with rate $\gamma > 0$ and volatility $\sigma \in \mathbb{R}$, and $W_n(t)$ being a Wiener process. The Ornstein-Uhlenbeck process is used to enhance the smoothness of noise evolution and make the noise more realistic than white noise in speed-based models (see [2] for a more detailed description). The

OV function is assumed positive, increasing, and bounded by the maximal desired speed.

In contrast to the totally asymmetric model [2], the OV function depends on a weighted average between the distance to the predecessor $\Delta x_n(t)$ and the distance to the follower $\Delta x_{n-1}(t)$, adjusted by a dimensionless, fine-tuning asymmetry parameter $\alpha \in \mathbb{R}$. The totally asymmetric model is restored if $\alpha = 0$. Conversely, the speed function only depends on the distance to the follower if $\alpha = -1$, whereas it is symmetric and depends on the arithmetic mean of the distances to the follower and the predecessor if $\alpha = -1/2$. Intuitively, the cases $\alpha > 0$ lead to homogenization dynamics, as a large distance ahead and a small distance behind results in a higher speed, while a small distance ahead and a large distance behind results in a lower speed and inversely.

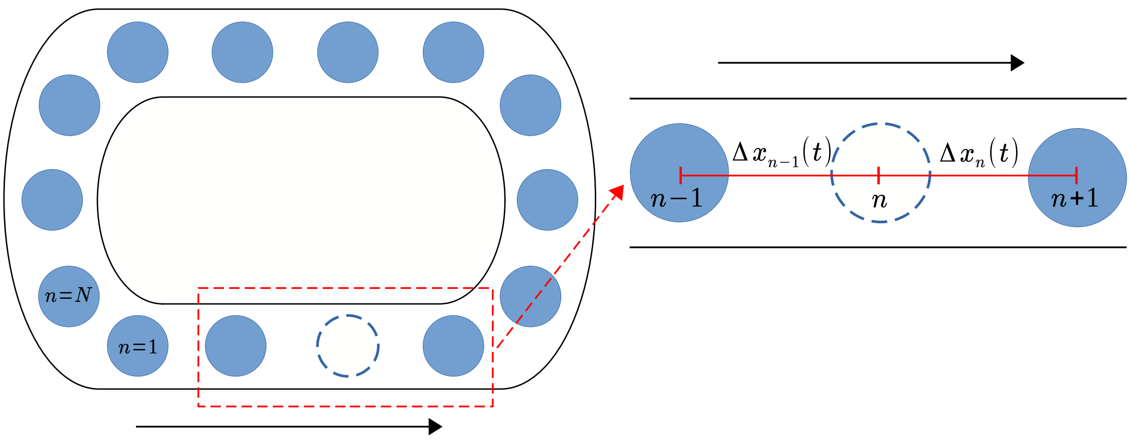

Figure 2: Scheme of the system with periodic boundary conditions. $\Delta x_n(t)$ is the distance of the pedestrian n to the predecessor at time t, while $\Delta x_{n-1}(t)$ is the distance to the follower.

The OV function $F : \mathbb{R} \mapsto \mathbb{R}^+$ includes classical parameters related to the pedestrian characteristics and behaviors, such as the desired speed $v_0 > 0$, the desired time gap $T > 0$, and the pedestrian size (circle width) $\ell > 0$. A typical OV function is the following bounded linear function:

$$F(x) = \min\left\{v_0, \frac{x_n(t) - \ell}{T}\right\} \tag{3}$$

that we approximate using the smoothed Log-Sum-Exp function [40] given by:

$$F_\varepsilon(x) = -\varepsilon \log\left(\exp\left(-\frac{v_0}{\varepsilon}\right) + \exp\left(-\frac{x_n(t) - \ell}{T\varepsilon}\right)\right), \qquad \text{as} \quad \varepsilon \to 0. \tag{4}$$

In the following, we set the speed smoothing ε to 0.01 m/s.

4 Linear Stability Analysis

We first examine the linear stability of the deterministic first-order model (Equation (2)) to determine possible values of parameters. Applying stability analysis allows us to investigate the behavior of the proposed first-order deterministic model (Equation (2)). Therefore, we need to determine the behavior of a solution to the differential equation as follows.

In general, suppose a linear differential equation given by the form:

$$f'(t) = af(t), \qquad \text{where } t \in [0, \infty) \text{ and } a \in \mathbb{R} \tag{5}$$

The general solution of Equation (5) above is:

$$f(t) = be^{at}, \tag{6}$$

with $b = f(0)$. Indeed, we have in this case:

$$f'(t) = abe^{at} = af(t). \tag{7}$$

So, $f'(t)$ depends on the value of the constant a. It converges if and only if the value of a is non-positive, i.e.,

$$a < 0, \tag{8}$$

otherwise the system will collapse.

Focusing on the interactive part of the model, the single-file dynamics for the n-th pedestrian is given by:

$$\begin{aligned} \dot{x}_n(t) &= \frac{1}{T}(\Delta x_n(t) + \alpha(\Delta x_n(t) - \Delta x_{n-1}(t))) \\ &= \frac{1}{T}((1+\alpha)\Delta x_n(t) - \alpha \Delta x_{n-1}(t)). \end{aligned} \tag{9}$$

By substituting $\Delta x_n(t) = x_{n+1}(t) - x_n(t)$ and $\Delta x_{n-1}(t) = x_n(t) - x_{n-1}(t)$ into Equation (9) we obtain:

$$\begin{aligned} \dot{x}_n(t) &= \frac{1}{T}((1+\alpha)x_{n+1} - (1+2\alpha)x_n + \alpha x_{n-1}) \\ &= \frac{1}{T}(1+\alpha)x_{n+1} - \frac{1}{T}(1+2\alpha)x_n + \frac{1}{T}\alpha x_{n-1} \\ &= -\frac{1}{T}(1+2\alpha)x_n + \frac{1}{T}((1+\alpha)x_{n+1} + \alpha x_{n-1}) \\ &= ax_n + C(x_{n+1}, x_{n-1})\ dt \end{aligned} \tag{10}$$

with:

$$a = -\frac{1}{T}(1+2\alpha), \tag{11}$$

and:

$$C(x_{n+1}, x_{n-1}) = \frac{1}{T}((1+\alpha)x_{n+1} + \alpha x_{n-1}). \tag{12}$$

Then the system will be stable if the stability condition $a < 0$ is satisfied (see condition (8)), which is given by

$$-\frac{1}{T}(1 + 2\alpha) < 0,$$

which is equivalent to:

$$\alpha > -1/2, \tag{13}$$

as $T > 0$.

Interestingly, the critical value is:

$$\alpha_C = -1/2 \tag{14}$$

corresponds to a symmetric case where the distance in the OV function is the arithmetic mean of the distances to the nearest neighbors in front and behind. Setting $\alpha > -1/2$ makes the weight for the distance ahead higher than the weight for the distance behind. Therefore, the following model is only stable if the interaction model is asymmetric, giving more importance to the distance to the neighbor in front.

5 Parameters Calibration

5.1 Single-file Movement Datasets and Data Preparation

Two different experimental datasets are used to statistically estimate the parameters of the model and for comparison with the simulation results. The first data sample is the one-dimensional dataset of Paetzke et al. [24]. Several experiments were conducted in Düsseldorf, Germany in 2021 to study the influence of gender on pedestrian movement. The pedestrians were instructed to move in an oval corridor one after the other without haste and overtaking (see Figure 3). We select the mixed alternating experiment for the parameters' calibration. The data includes different experimental runs with a pedestrian number varying between $N = 8, 16, 20, 24, 32, 36, 40$. That ensures obtaining different ranges of variation of distances between pedestrians, and speeds. The data of each pedestrian in the different experimental runs are collected and labeled with pedestrian ID (unique number). This data will be used to estimate individually the model's parameters (see Section 5.2). For more details on the experiment, refer to the article [24].

The second experiment dataset used for parameter calibration and validation of the numerical simulation is the single-file movement dataset by Ziemer et al. [41]. The experiment (see Figure 4), conducted in Germany within the project BaSiGo, focuses on the analysis of pedestrians' dynamic moving in an oval system with periodic boundary conditions. We use in the following the data of the experiments with $N = 15, 30, 47, 52, 55, 59$ participants. Evaluating the model with two different datasets will ensure that the model is reliable and generalizes well to new data. Table 1 summarizes the main information about the experiments.

The trajectory data from the experiments is used to calculate the pedestrian positions $x_n(t)$, the speed $v_n(t)$, and the distance in the front $\Delta x_n(t)$ and behind

Figure 3: Overhead view of the CroMa single-file movement experiment run $N = 20$.

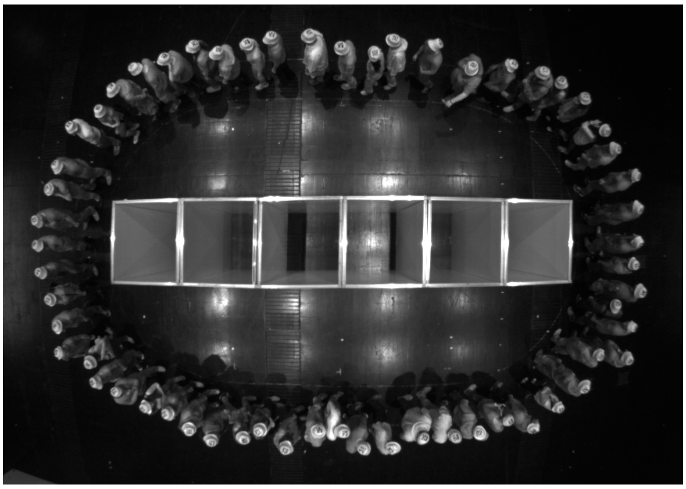

Figure 4: Overhead view of the BaSiGo single-file movement experiment run $N = 59$.

$\Delta x_{n-1}(t)$. Here is the equation of the pedestrian's speed:

$$v_n(t) = \frac{x_n(t + \Delta t/2) - x_n(t - \Delta t/2)}{\Delta t}, \tag{15}$$

where Δt short time interval around t (10 frames, i.e., 0.4 s).

5.2 Nonlinear Least Squares Estimates of the Parameters

The calibration of the proposed model (2) is necessary for making quantitative predictions. To achieve this, we need to adjust the models' parameters to fit the different samples of experimental data. We use the nonlinear least squares method

Experiment	Location, date	Geometry length [m]	Number of participants	Framerate [fps]	Investigation	Pedestrian identification across runs
CroMa	Düsseldorf, Germany (2021)	14.97	$N = 8$, 16, 20, 24, 32, 36, 40	25	Gender factor (mixed)	✓
BaSiGo	Düsseldorf, Germany (2013)	26.84	$N = 15$, 30, 47, 52, 55, 59	16	Congested dynamic	

Table 1: Table summarizing CroMa and BaSiGo datasets used for parameter calibration and model validation.

to estimate the parameters $p = (v_0, T, \ell, \alpha)$ related to the deterministic part of the model (see (2) and (4)). The non-linear speed model reads as follows:

$$M_p(\Delta x_n, \Delta x_{n-1}) = F_{v_0,T,\ell}\big(\Delta x_n + \alpha(\Delta x_n - \Delta x_{n-1})\big), \tag{16}$$

with F the smoothed optimal velocity function given in (4). The regression is nonlinear since the OV function is sigmoidal. Then, using an experimental sample of K observations of individual speed and distances in front and behind $(s_k, \Delta x_k, \Delta x_k^0)$ where $k = 1, \dots, K$, we estimate the parameters p by minimizing the difference to the square between the observed speeds and the model predictions:

$$\tilde{p} = \arg\min_p \sum_{k=1}^{K} \big(s_k - M_p(\Delta x_k, \Delta x_k^0)\big)^2. \tag{17}$$

The model residuals are the variables:

$$R_k(\tilde{p}) = s_k - M_{\tilde{p}}(\Delta x_k, \Delta x_k^0) \tag{18}$$

The least squares estimates minimize the sum of squared residuals. In the following sections, we begin by presenting the global parameter estimates over the full data samples, followed by individual estimates calculated for each pedestrian. Subsequently, we delve into a detailed discussion of the estimates for α.

5.2.1 Global Parameter Estimates

Figure 5 illustrates the global parameter estimations over the full samples for the totally asymmetric model (with initialized $\alpha = 0$) and the proposed asymmetric model (with estimated α) without noise (presenting the deterministic part of the model). Note that for the initial model with $\alpha = 0$, the speed solely depends on the distance in front. The optimal velocity function appears directly (see Eq. (3) and figure 5, left panel). On the other hand, the extended speed model depends on the distances in front and behind, allowing to reproduction of a certain variability even in the deterministic framework (see figure 5, right panel). The results show

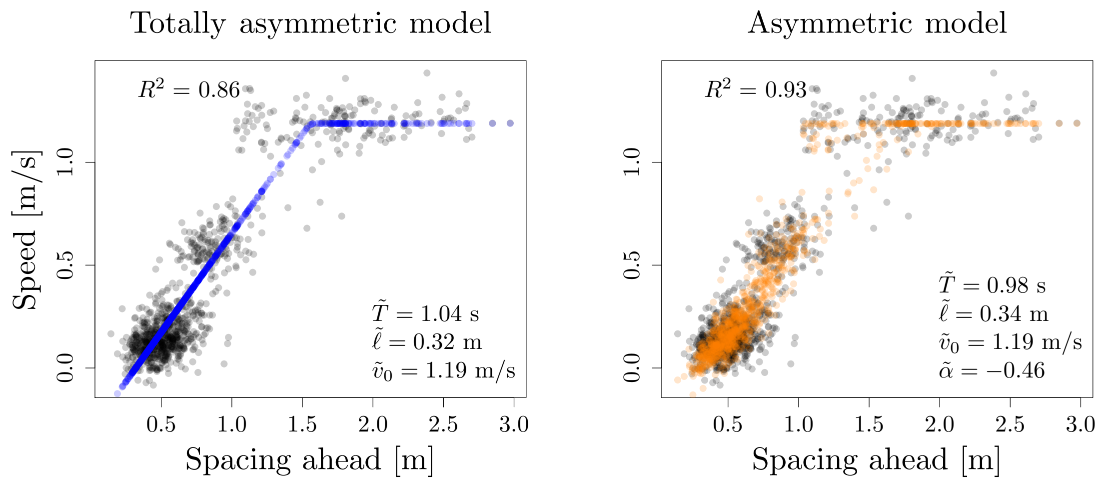

Figure 5: Global estimates of the model's parameters (without noise) using nonlinear least squares. The scatter plots of the fundamental diagram for the BaSiGo experimental dataset and the predictions of the totally asymmetric model (left panel) and the asymmetric model (right panel) are presented. The parameters' estimates (T, ℓ, v_0) of the optimal velocity are close to each other for both models. The asymmetric model reproduces the variability of the fundamental diagram and improves the prediction. Note that only 16% of the data samples are shown in the scatter plots to improve the readability of the figure.

that the estimates of the parameters (T, ℓ, v_0) for the optimal velocity function are equivalent to the totally asymmetric and asymmetric models. The estimates for T are 1.04 s and 0.98 s, and for ℓ are 0.32 m and 0.34 m for totally asymmetric and asymmetric models, respectively. While, the desired velocity, v_0, is 1.19 m/s for both models. Therefore, the model extension with the fine-tuning parameter α does not affect the shape of the fundamental (distance-speed) relationship. We note that the estimated value of $\alpha = -0.46$ is negative and close to the critical stability condition ($\alpha_C = -1/2$). Furthermore, we observe that the asymmetric model with an estimated α has the highest R^2 value ($R^2 = 0.93$) compared to the totally asymmetric model ($R^2 = 0.86$). Indeed, it also recovers part of the variability of the distance-speed relationship. The proposed model captures the variability of the data points better than the totally asymmetric model. However, this is not surprising as the asymmetric model has one more parameter.

The distributions of the residuals of both models are compact as shown in Figure 6. This means that the least squares estimates are close to the maximum likelihood estimates. The distribution for the asymmetric model is slightly more concentrated with a lower standard deviation. The standard deviation of the residual is approximately 0.15 m/s for the totally asymmetric model while it is 0.11 m/s for the new asymmetric model. A Fisher test for equality of the variance allows rejecting the equality hypothesis without any doubt (p-value smaller than 2.2e−16). Furthermore, assuming that the residuals are normally distributed, the Akaike information criterion:

$$\text{AIC} = 2k - 2\log(\tilde{\mathcal{L}})$$

with k the number of parameters (3 and 4 for the totally asymmetric and asym-

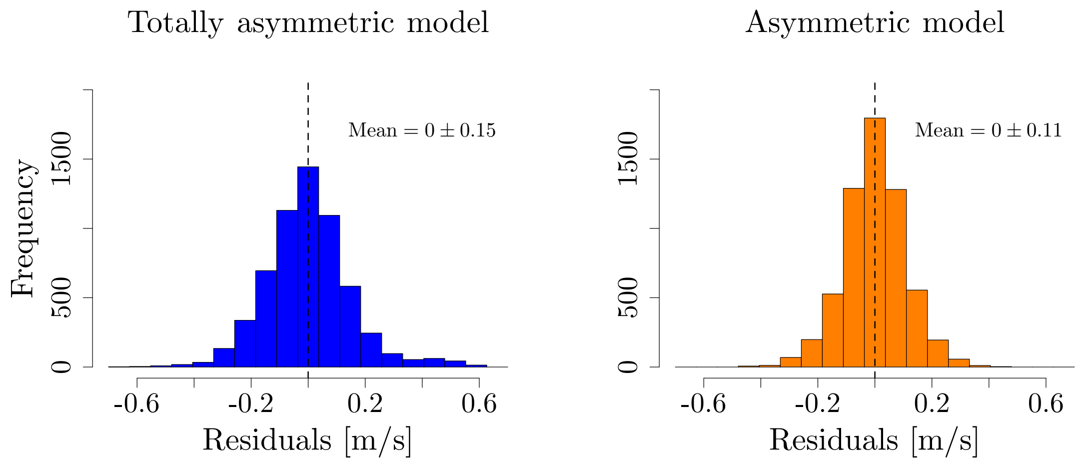

Figure 6: Histograms of the residuals for the totally asymmetric model (left panel) and the asymmetric model (right panel). The distribution for the asymmetric model is slightly more concentrated.

metric models, respectively) and $\tilde{\mathcal{L}}$ the maximum likelihood, is much smaller for the asymmetric model (AIC $= -9632.5$) than for the initial totally asymmetric model (AIC $= -5732$). This confirms the enhancements of the new model even by taking into account that it includes one more parameter. Therefore, the improvements gained with the new parameter of the asymmetric model are statistically significant.

Finally, note that our observations are extracted from the trajectories and are time-dependent. The generalized least squares estimates, taking into account the (linear) time dependence, are close to the ordinary least squares estimates.

5.2.2 Individual Parameter Estimates

The CroMa experimental sample offers the possibility to identify the pedestrians in each experimental run. This allows the model parameters to be estimated individually for each pedestrian across all density levels. The estimates for the parameters (T, ℓ, v_0) of the optimal velocity function are close to those obtained using the BaSiGo dataset (see Figure 7). The legend in the right panel gives the mean values over all estimates of pedestrians' individual parameters.

The histograms of the individual parameter estimates are depicted in Figure 8. The variation ranges for parameter estimates of the optimal velocity function are reasonable. For the desired time gap $\tilde{T}$ the values range from 0.6 to 1.6 s. While for the pedestrian size $\tilde{\ell}$ the value ranges from 0.2 to 0.5 m, and for the desired speed $\tilde{v}_0$ from 0.9 to 1.6 m/s. Drawing attention to intriguing findings, that the individual estimates for the parameter α are systematically non-positive and may even be smaller than the critical stability threshold $\alpha_C = -1/2$.

A summary of the different estimates for the parameters of the totally asymmetric and asymmetric models is given in Table 2. It is noteworthy that the estimates are very similar for the different datasets (BaSiGo and CroMa) and estimation methods (global and individual). The parameters' values of the optimal velocity function

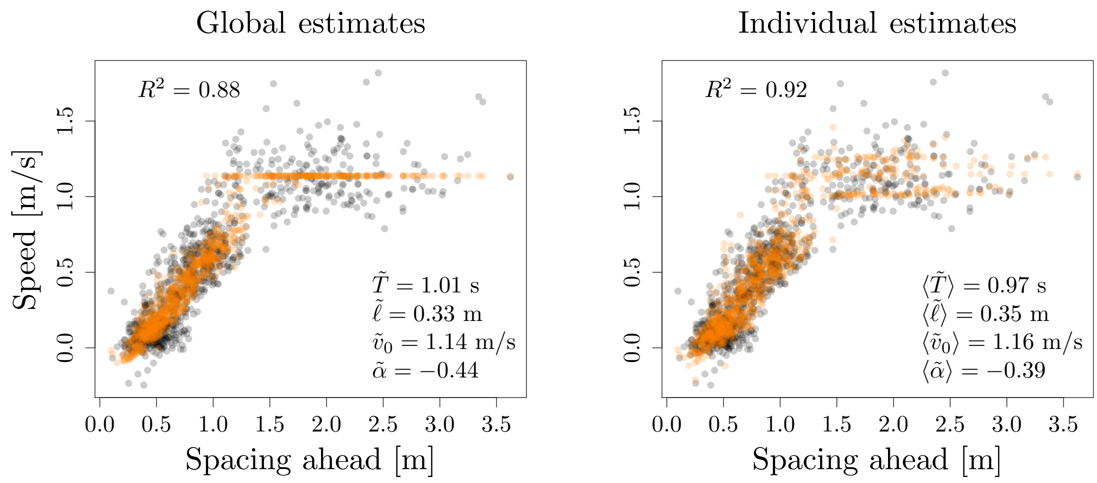

Figure 7: Global (left panel) and individual (right panel) least squares estimates of the parameters using the CroMa dataset. The values for individual estimates are the averages for all the pedestrians. The parameter estimates are relatively stable. Note that only 16% of the observations and predictions are presented to improve the readability.

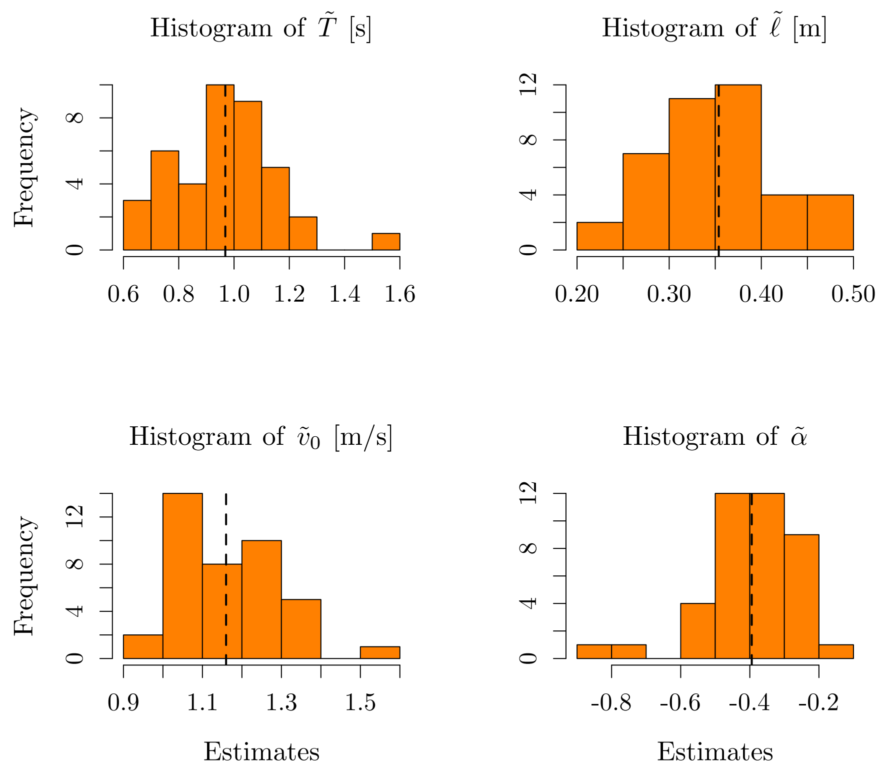

Figure 8: Histograms of the parameter estimates by individual nonlinear least squares using the CroMa dataset.

for both the totally asymmetric and asymmetric models are approximately similar. These results confirm the accuracy of the estimates obtained and the characteristic behavior of single-file pedestrian motion.

	Global estimates			Individual estimates
	BaSiGo dataset		CroMa dataset	
	Totally asym. model ($\alpha = 0$)	Asymmetric model (estimated α)		
$\tilde{T}$ [s]	1.04	0.98	1.01	0.97 ± 0.18
$\tilde{\ell}$ [m]	0.32	0.34	0.33	0.35 ± 0.06
$\tilde{v}_0$ [m/s]	1.19	1.19	1.14	1.16 ± 0.13
$\tilde{\alpha}$	–	-0.46	-0.44	-0.39 ± 0.14
R^2	0.86	0.93	0.88	0.92
AIC	-5732	-9632.5	-6123.4	-8722.7

Table 2: Table summarizing the statistical estimates of the models' parameters for global/individual estimates, totally asymmetric, and proposed models. The values for the individual estimates have the form $X \pm Y$ with X the mean value and Y the empirical standard deviation over all the individual pedestrian estimates. The parameter estimates are close to each other whatever the sample and method used. The AIC is calculated over an identical sample size of 6000 observations.

5.2.3 Remarks on Estimation of α

The estimates for the asymmetry parameter α are systematically negative and close to the critical stability value $\alpha_C = -1/2$ (see 13). However, simulation results show that positive values for α, typically $\alpha = 1$, provide more realistic dynamics, especially regarding pedestrian overlap and backward movement when stop-and-go waves arise.

In fact, the low estimates for α mainly result from simple kinematic effects to single file motion, regardless of the dynamical model. Assuming that the OV function $F : s \mapsto F(s) = s/T$ is linear, the cost function in the least squares estimates reads for the parameter α:

$$f(\alpha) = \sum_{k=1}^{K} \Big(v_k - \frac{1}{\tilde{T}} \big(\Delta x_k + \alpha(\Delta x_k - \Delta x_k^0)\big) \Big)^2 \tag{19}$$

and the derivative is given by:

$$f'(\alpha) = \frac{-2}{\tilde{T}} \sum_{k=1}^{K} (\Delta x_k - \Delta x_k^0) \Big(v_k - \frac{1}{\tilde{T}} \big(\Delta x_k + \alpha(\Delta x_k - \Delta x_k^0)\big) \Big). \tag{20}$$

The function f being convex, it is minimal if:

$$f'(\tilde{\alpha}) = 0 \quad \Leftrightarrow \quad \tilde{\alpha} = \frac{\sum_{k=1}^{K} (\Delta x_k - \Delta x_k^0)(v_k \tilde{T} - \Delta x_k)}{\sum_{k=1}^{K} (\Delta x_k - \Delta x_k^0)^2}. \tag{21}$$

The probabilistic distribution of the distances ahead and behind can reasonably be assumed to be identical. Assuming further that these distances and the speed are statistically independent, i.e., that there is no relationship between speed and distances, we asymptotically obtain:

$$\tilde{\alpha} \to -1/2 \qquad \text{as} \qquad K \to \infty, \tag{22}$$

since:

$$\frac{\sum_{k=1}^{K}(\Delta x_k - \Delta x_k^0) v_k \tilde{T}}{\sum_{k=1}^{K}(\Delta x_k - \Delta x_k^0)^2} \to 0, \tag{23}$$

while:

$$-\frac{\sum_{k=1}^{K}(\Delta x_k - \Delta x_k^0)\Delta x_k}{\sum_{k=1}^{K}(\Delta x_k - \Delta x_k^0)^2} = \frac{-\sum_{k=1}^{K}\Delta x_k^2 - \Delta x_k \Delta x_k^0}{\sum_{k=1}^{K}\Delta x_k^2 + (\Delta x_k^0)^2 - 2\Delta x_k \Delta x_k^0} \to -1/2, \tag{24}$$

as $K \to \infty$. The kinematic relationships of the single-file motion dominate and bring the statistical estimate for α close to the critical stability condition for which the model is symmetric. The fine-tuning effects of the asymmetric mechanisms weighted by α occur at a lower level, through the interdependence between the distances and the speed. Therefore, the statistical estimate of the asymmetry parameter α is strongly influenced by the kinematic relationship of the single-file movement. This can lead to misleading calibration values for this parameter. In the following simulation analysis, we manually calibrate α and observe that positive values, e.g., $\alpha = 1$, give more realistic dynamics.

6 Simulation Results

6.1 Simulation Setup

We numerically simulate the asymmetric single-file pedestrian model using an Euler-Maruyama scheme. The numerical solver reads:

$$\begin{cases} x_n(t+\delta t) = x_n(t) + \delta t F\big(\Delta x_n(t) + \alpha(\Delta x_n(t) - \Delta x_{n-1}(t))\big) + \delta t \xi_n(t), \\ \xi_n(t+dt) = \xi_n(t)(1-\delta t\gamma) + \sqrt{\delta t}\sigma Z_n(t), \end{cases} \tag{25}$$

with the time step $\delta t = 0.01$ s and independent normal random variables $(Z_n(t),\ t = m\delta t,\ m \in \{0,1,2,\ldots\})_n$. Here F is the smoothed OV function given in Equation (4) with $v_0 = 1.19$ m/s, $T = 0.98$ s and $\ell = 0.34$ m. The speed smoothing is equal to $\varepsilon = 0.01$ m/s. For the noise parameters, we use the same estimates as [2] in the simulation, namely $\sigma = 0.09$ ms$^{-3/2}$ and $\gamma = 0.23$ s^{-1}. The values for α will be set manually, ranging from -0.25 to 2. The size of the geometry and number of pedestrians are set as in the BaSiGo and CroMa experiences. The initial condition is uniform with speeds zero.

6.2 Assessing the Asymmetry Parameter by Simulation

We assess the asymmetry parameter α by estimating the parameters using synthetic datasets obtained by simulation. The aim is to evaluate how strong the influence of the kinematic single-file relationships on the least squares estimates for α. The scatter plots of real and synthetic data with corresponding least squares parameter estimates are shown in Figure 9 and Table 3.

		Synthetic data				
	BaSiGo	$\alpha = -0.25$	$\alpha = 0$	$\alpha = 0.25$	$\alpha = 1$	$\alpha = 2$
$\tilde{T}$ [s]	0.98	1.06	1.06	1.04	1.05	1.04
$\tilde{\ell}$ [m]	0.34	0.31	0.32	0.32	0.32	0.32
$\tilde{v}_0$ [m/s]	1.19	1.14	1.13	1.11	1.07	1.08
$\tilde{\alpha}$	-0.46	-0.45	-0.49	-0.5	-0.5	-0.49
R^2	0.92	0.92	0.94	0.95	0.96	0.97

Table 3: Table summarizing the estimates of the model's parameters by nonlinear least squares using the BaSiGo data set and synthetic data obtained by simulation with α ranging between -0.25 and 2. The symbols $\tilde{T}$, $\tilde{\ell}$, $\tilde{v}_0$, and $\tilde{\alpha}$ are the parameter values estimated by least squares. Note that although the setting for α ranges from -0.25 to 2 in the simulations, the estimates remain stable around -0.5 due to kinematic single-file effects.

We can clearly observe in the figure that decreasing α increases the scattering of the data points. The simulation with $\tilde{\alpha} = -0.46$ as statistically estimated, shows an unrealistically larger scatter.

As expected, the least squares estimates for the asymmetry parameter α remain constant, close to the critical stability condition $\alpha_C = -1/2$. This holds even when $\alpha \gg 0$ in the model, confirming the predominance of the kinematic single-file relationships in the dynamics and the limited significance of the statistical estimates. The estimates of the parameter (T, ℓ, v_0) of the OV function (4) are also stable. Only the estimates for the desired speed v_0 slightly decrease as α increases due to the nonlinear shape of the OV function.

6.3 Main Simulation Results

In this section, we compare the real data of the BaSiGo experiment with the simulation results of the totally asymmetric model and the new asymmetric model. The parameters of the deterministic speed models are set as follows: the desired speed is $v_0 = 1.19$ m/s, the desired time gap is $T = 0.98$ s, the pedestrian size is $\ell = 0.34$ m, while the noise parameters are equal to $\sigma = 0.09$ ms$^{-3/2}$ and $\gamma = 0.23$ s^{-1}. The dimensionless asymmetry parameter α is set to zero for the totally asymmetric model whereas it is equal to one for the new asymmetric model. Several simulation runs

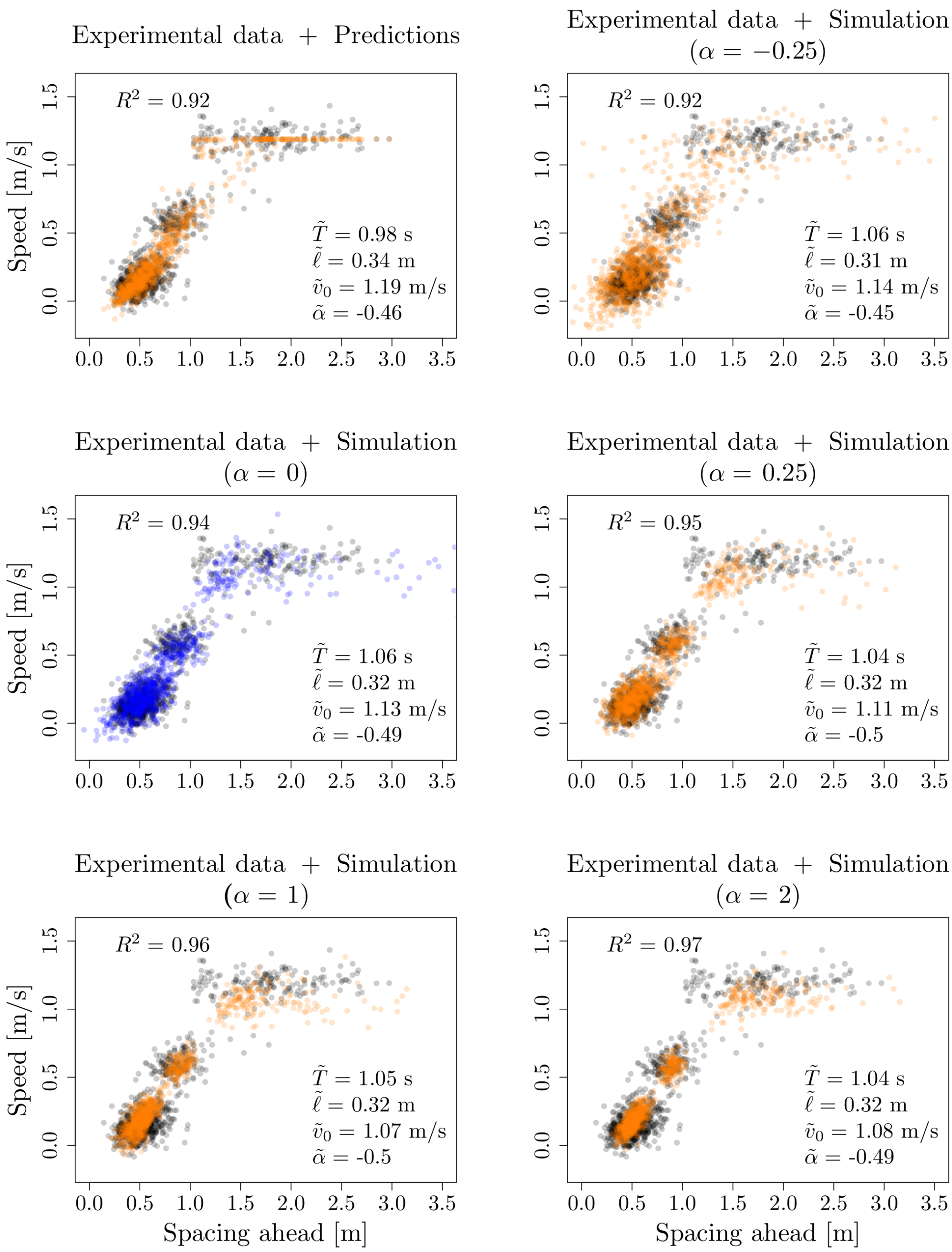

Figure 9: Least squares parameter estimates and pedestrian distance-speed scatter plots for the BaSiGo experiment (grey dots), the model prediction (upper left plot), and simulation results for α between -0.25 and 2 (remaining plots). The estimates for the asymmetry parameter α remain constant, close to the critical stability condition $\alpha_C = -1/2$, even for the synthetic data when $\alpha \gg 0$. Note that only 16% of data points are presented.

are carried out with different numbers of pedestrians $N = 15$, 30, 47, 52, 55, and 59 as in the BaSiGo experiment.

6.3.1 Fundamental Diagram

We compare the fundamental relationship between the distance ahead and the speed, as well as the distributions of the speed and distance individually (see Figure 10). It is noteworthy that the asymmetric model better shapes the data point scatter of the fundamental diagram compared to the totally asymmetric model (see Figure 10, upper panels). In both real and synthetic data obtained with the asymmetric model, three main clusters can be observed. These clusters are also present in the totally asymmetric model, but they are less pronounced.

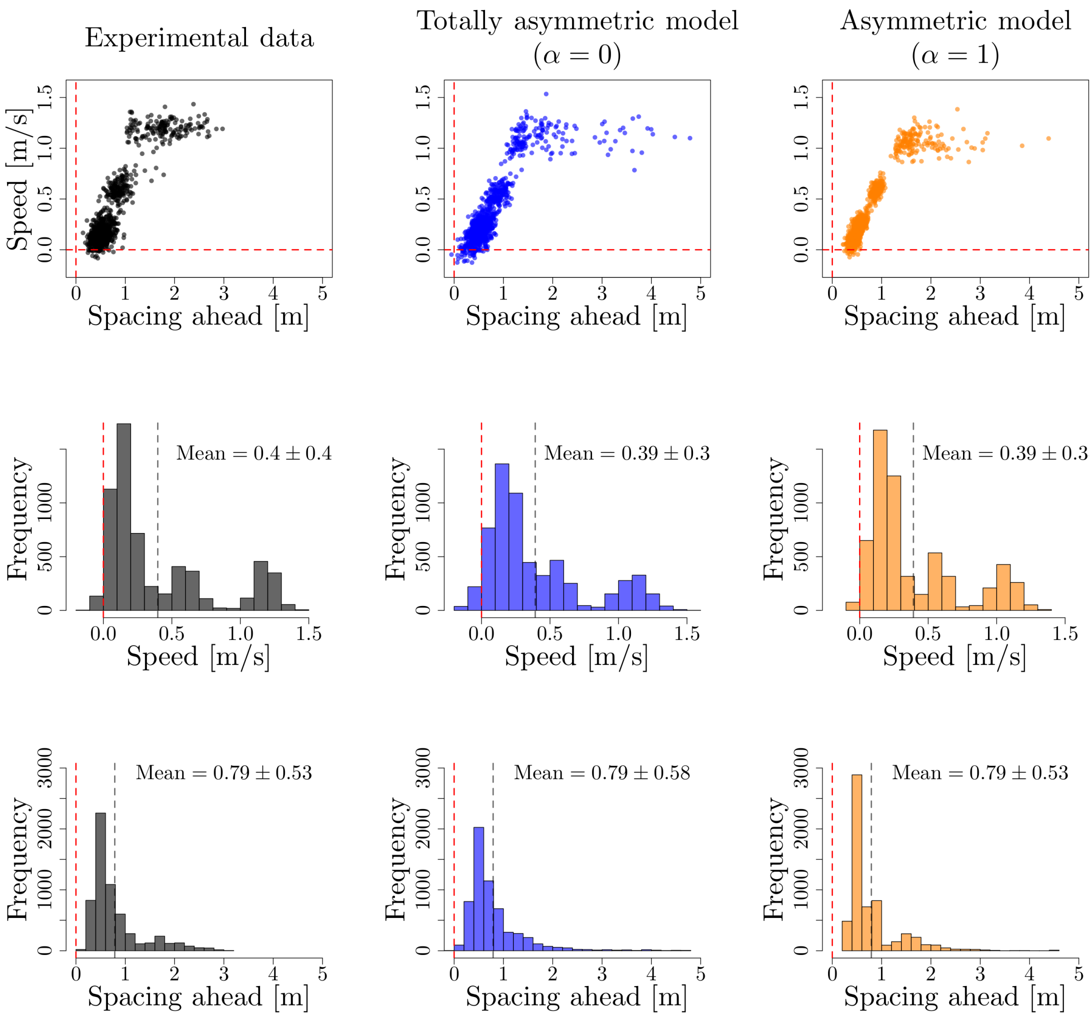

Figure 10: Distance-speed scatterplot (upper panels), speed histogram (middle panels) and spacing ahead histogram (bottom panels) of BaSiGo experimental data (left panel) and the simulation results of totally asymmetric ($\alpha = 0$, central panels) and asymmetric ($\alpha = 1$, right panels) models for runs $N = 15, 30, 47, 52, 55, 59$. Note that only 16% of the data samples were used in the scatter plots. The red dashed line is located on zero to indicate the negative values of the speed and distance ahead.

The marginal distributions of the speed and distance confirm the improvements obtained with the asymmetric interaction model. Regarding the speed distribution, both the real data and simulation results from the new model exhibit close similarities, with three modes of identical amplitude. Conversely, the shape of the three modes is less pronounced in the totally asymmetric model (see Figure 10, middle panels). As for the distance distributions, they appear relatively compact and similar for the real data and the asymmetric model, with distances less than 3 and 4 meters, respectively. In contrast, the totally asymmetric model distance distributions have an unrealistically large tail with distances up to 8 meters (see Figure 10, bottom panels). Furthermore, both the real data and the simulation results from the asymmetric model show a minimal occurrence of negative values for speed and distance compared to the totally asymmetric model (see the left tail of the distributions in Figure 10, middle and lower panels).

6.3.2 Space-Time Diagram

In this section, we compare the real (BaSiGo experiment) and synthetic single-file trajectories obtained from the totally asymmetric and asymmetric models with 59 participants (see Figure 11). It is observed that the totally asymmetric model shows

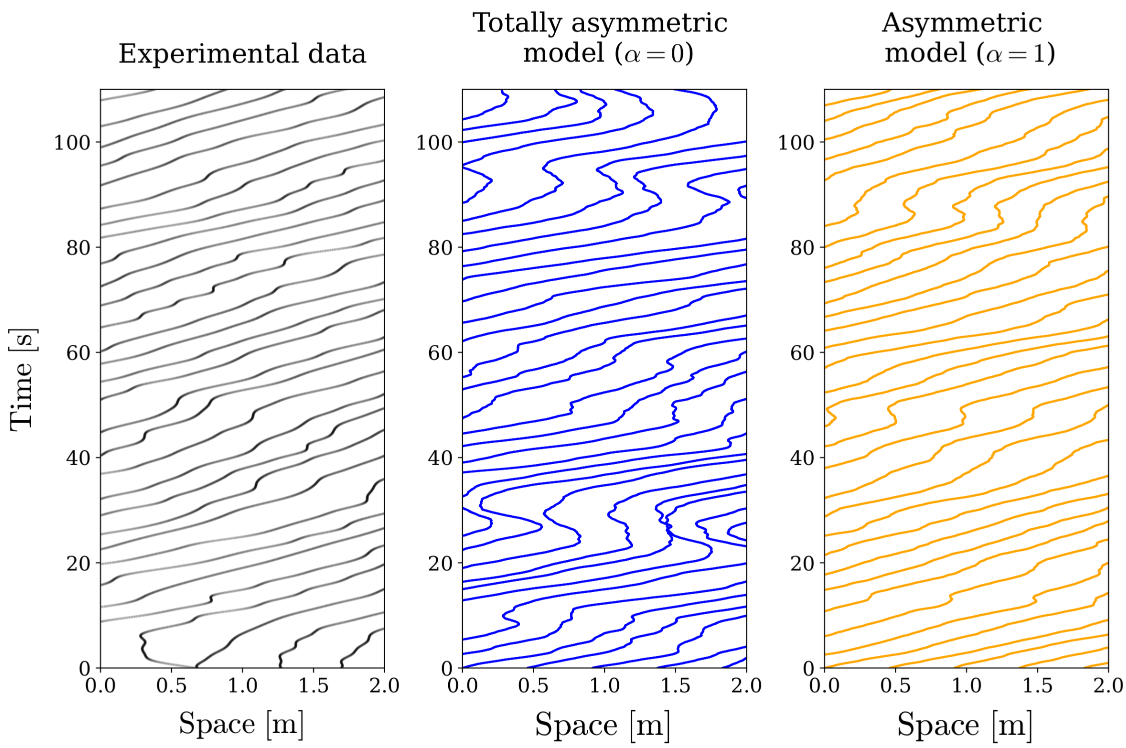

Figure 11: Trajectories of $N = 59$ pedestrian walking on a ring of length 27 m observed over a segment of length 2 m. From left to right: real data (BaSiGo experiment), totally asymmetric model ($\alpha = 0$), and asymmetric model ($\alpha = 1$), respectively.

more backward movement with negative speed and overlap compared to the real data. This aligns with the previously mentioned findings regarding the left tail of the speed and distance distributions, which spread out in the totally asymmetric model (refer to Figure 10, middle and bottom panels). The simulations for the asymmetric model with $\alpha = 1$ show fewer backward movements, making the stop-and-go waves qualitatively more realistic. This improvement is obvious in the crowded experiment with 59 participants.

Another enhancement introduced by our proposed model is to make the noise parameters constant. In previous work [2], the noise parameters (σ and γ) are state-dependent, meaning that multiple values for the noise parameters (σ or γ) are estimated depending on the distance class (refer to Figure 7 in the paper [2]). By introducing the distance to the follower, we simplify the calibration process for the noise parameters, making the calculations much easier.

7 Conclusions

We present an original asymmetric stochastic model describing the movement of pedestrians in one-dimensional space (single-file motion). Taking inspiration from statistical analysis [22] and observation of coordination in pedestrian single-file motion [23], we include the distance to the follower in the OV model, resulting in an asymmetric interaction model including a fine-tuning asymmetry parameter α. Statistical estimates of the model using experimental data enable parameter calibration and interpretation. They also demonstrate that the enhancement brought by the new parameter is statistically significant. The comparison of the experimental data and synthetic data of the improved model under different settings of α, specifically $\alpha = 0$ and $\alpha = 1$, shows a strong agreement between the asymmetric model results and the experimental data. The simulations performed with positive α exhibit reduced backward movements, resulting in stop-and-go waves that closely resemble the experimental data. Additionally, the model describes a realistic fundamental diagram and, in particular, its scattering. Further evaluation in terms of validation and verification to assess the model's overall performance will be undertaken in future work. The proposed model should also be benchmarked against various models found in the literature.

CRediT authorship contribution statement

Rudina Subaih: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing original draft, Writing – review & editing. **Antoine Tordeux:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – review & editing, Supervision.

Declaration of competing interest

We wish to confirm that there are no known conflicts of interest associated with this publication. This work was supported by the German Federal Ministry of Education and Research (BMBF: funding number 01DH16027) within the framework of the Palestinian-German Science Bridge project.

Data availability

Data will be made available on request.

Acknowledgment

This work was supported by the German Federal Ministry of Education and Research (BMBF: funding number 01DH16027) within the framework of the Palestinian-German Science Bridge project. All authors have read and agreed to the published version of the manuscript.

References

[1] Jakob Cordes, Mohcine Chraibi, Antoine Tordeux, and Andreas Schadschneider. "Time-To-Collision Models for Single-File Pedestrian Motion". In: *Collective Dynamics* 6 (2021), pp. 1–10.

[2] Antoine Tordeux and Andreas Schadschneider. "White and relaxed noises in optimal velocity models for pedestrian flow with stop-and-go waves". In: *Journal of Physics A: Mathematical and Theoretical* 49.18 (2016), p. 185101.

[3] Mohcine Chraibi, Takahiro Ezaki, Antoine Tordeux, Katsuhiro Nishinari, Andreas Schadschneider, and Armin Seyfried. "Jamming transitions in force-based models for pedestrian dynamics". In: *Physical Review E* 92.4 (2015), p. 042809.

[4] Samuel Lemercier, Asja Jelic, Richard Kulpa, Jiale Hua, Jérôme Fehrenbach, Pierre Degond, Cécile Appert-Rolland, Stéphane Donikian, and Julien Pettré. "Realistic following behaviors for crowd simulation". In: *Computer Graphics Forum*. Vol. 31. Wiley Online Library. 2012, pp. 489–498.

[5] Hua Kuang, Yanhong Fan, Xingli Li, and Lingjiang Kong. "Asymmetric effect and stop-and-go waves on single-file pedestrian dynamics". In: *Procedia engineering* 31 (2012), pp. 1060–1065.

[6] Andrea Portz and Armin Seyfried. "Analyzing stop-and-go waves by experiment and modeling". In: *Pedestrian and Evacuation Dynamics*. Springer, 2011, pp. 577–586.

[7] Mohcine Chraibi, Armin Seyfried, and Andreas Schadschneider. "Generalized centrifugal-force model for pedestrian dynamics". In: *Physical Review E* 82.4 (2010), p. 046111.

[8] Tobias Kretz. "On oscillations in the social force model". In: *Physica A: Statistical Mechanics and its Applications* 438 (2015), pp. 272–285.

[9] Ioannis Karamouzas, Brian Skinner, and Stephen J Guy. "Universal power law governing pedestrian interactions". In: *Physical review letters* 113.23 (2014), p. 238701.

[10] Antoine Tordeux, Mohcine Chraibi, and Armin Seyfried. "Collision-free speed model for pedestrian dynamics". In: *Traffic and Granular Flow'15*. Springer. 2016, pp. 225–232.

[11] Jan Ondřej, Julien Pettré, Anne-Hélène Olivier, and Stéphane Donikian. "A synthetic-vision based steering approach for crowd simulation". In: *ACM Transactions on Graphics (TOG)* 29.4 (2010), pp. 1–9.

[12] Andreas Schadschneider. “Cellular automaton approach to pedestrian dynamics-theory”. In: *In: Schreckenberg M, Sharma SD (eds) Pedestrian and evacuation dynamics. Springer, Berlin/Heidelberg* (2001), pp. 75–86.

[13] Dirk Helbing and Peter Molnar. “Social force model for pedestrian dynamics”. In: *Physical review E* 51.5 (1995), p. 4282.

[14] K. Hirai and K. Tarui. “A simulation of the behavior of a crowd in panic”. In: *Proc. of the 1975 international conference on cybernetics and society*. San Francisco, 1975, pp. 409–411.

[15] Nicola Bellomo, Benedetto Piccoli, and Andrea Tosin. “Modeling crowd dynamics from a complex system viewpoint”. In: *Mathematical models and methods in applied sciences* 22.supp02 (2012), p. 1230004.

[16] Roger L Hughes. “A continuum theory for the flow of pedestrians”. In: *Transportation Research Part B: Methodological* 36.6 (2002), pp. 507–535.

[17] Roger L Hughes. “The flow of human crowds”. In: *Annual review of fluid mechanics* 35.1 (2003), pp. 169–182.

[18] RL Hughes. “The flow of large crowds of pedestrians”. In: *Mathematics and Computers in Simulation* 53.4-6 (2000), pp. 367–370.

[19] Dirk Helbing. “A fluid dynamic model for the movement of pedestrians”. In: *arXiv preprint cond-mat/9805213* (1998).

[20] Leroy F Henderson. “On the fluid mechanics of human crowd motion”. In: *Transportation research* 8.6 (1974), pp. 509–515.

[21] Mohcine Chraibi, Antoine Tordeux, Andreas Schadschneider, and Armin Seyfried. “Modelling of pedestrian and evacuation dynamics”. In: *Encyclopedia of complexity and systems science* (2018), pp. 1–22.

[22] Rudina Subaih, Mohammed Maree, Antoine Tordeux, and Mohcine Chraibi. “Questioning the Anisotropy of Pedestrian Dynamics: An Empirical Analysis with Artificial Neural Networks”. In: *Applied Sciences* 12.15 (2022), p. 7563.

[23] Kevin W Rio, Christopher K Rhea, and William H Warren. “Follow the leader: Visual control of speed in pedestrian following”. In: *Journal of vision* 14.2 (2014), pp. 4–4.

[24] Sarah Paetzke, Maik Boltes, and Armin Seyfried. “Influence of Gender Composition in Pedestrian Single-File Experiments”. In: *arXiv preprint arXiv:2302.11168* (2023).

[25] Rudina Subaih, Mohammed Maree, Mohcine Chraibi, Sami Awad, and Tareq Zanoon. “Experimental investigation on the alleged gender-differences in pedestrian dynamics: A study reveals no gender differences in pedestrian movement behavior”. In: *IEEE access* 8 (2020), pp. 33748–33757.

[26] Akihiro Fujita, Claudio Feliciani, Daichi Yanagisawa, and Katsuhiro Nishinari. “Traffic flow in a crowd of pedestrians walking at different speeds”. In: *Physical Review E* 99.6 (2019), p. 062307.

[27] AATM Aw, Axel Klar, Michel Rascle, and Thorsten Materne. “Derivation of continuum traffic flow models from microscopic follow-the-leader models”. In: *SIAM Journal on applied mathematics* 63.1 (2002), pp. 259–278.

[28] Mohcine Chraibi, Ulrich Kemloh, Andreas Schadschneider, and Armin Seyfried. “Force-based models of pedestrian dynamics”. In: *Networks & Heterogeneous Media* 6.3 (2011), p. 425.

[29] Mohcine Chraibi. “Oscillating behavior within the social force model”. In: *arXiv preprint arXiv:1412.1133* (2014).

[30] Jakob Cordes, Andreas Schadschneider, and Antoine Tordeux. “The trouble with 2nd order models or how to generate stop-and-go traffic in a 1st order model”. In: *Traffic and Granular Flow 2019*. Springer. 2020, pp. 45–51.

[31] Ignacio Mariano Sticco, Guillermo Alberto Frank, Fernando Ezequiel Cornes, and Claudio Oscar Dorso. “A re-examination of the role of friction in the original Social Force Model”. In: *Safety science* 121 (2020), pp. 42–53.

[32] Antoine Tordeux and Armin Seyfried. “Collision-free nonuniform dynamics within continuous optimal velocity models”. In: *Physical Review E* 90.4 (2014), p. 042812.

[33] Minghui Ma, Wenjie Wang, Shidong Liang, Jiacheng Xiao, and Chaoteng Wu. “Improved Car-Following Model for Connected Vehicles Considering Backward-Looking Effect and Motion Information of Multiple Vehicles”. In: *Journal of Transportation Engineering, Part A: Systems* 149.2 (2023), p. 04022148.

[34] Dongfang Ma, Yueyi Han, Fengzhong Qu, and Sheng Jin. “Modeling and analysis of car-following behavior considering backward-looking effect”. In: *Chinese Physics B* 30.3 (2021), p. 034501.

[35] Guangyi Ma, Minghui Ma, Shidong Liang, Yansong Wang, and Hui Guo. “Nonlinear analysis of the car-following model considering headway changes with memory and backward-looking effect”. In: *Physica A: Statistical Mechanics and its Applications* 562 (2021), p. 125303.

[36] Da Yang, Peter Jin, Yun Pu, and Bin Ran. “Safe distance car-following model including backward-looking and its stability analysis”. In: *The European Physical Journal B* 86 (2013), pp. 1–11.

[37] HX Ge, HB Zhu, and SQ Dai. “Effect of looking backward on traffic flow in a cooperative driving car the following model”. In: *The European Physical Journal B-Condensed Matter and Complex Systems* 54 (2006), pp. 503–507.

[38] Akihiro Nakayama, Yūki Sugiyama, and Katsuya Hasebe. “Effect of looking at the car that follows in an optimal velocity model of traffic flow”. In: *Physical Review E* 65.1 (2001), p. 016112.

[39] Julien Monteil, Romain Billot, Jacques Sau, and Nour-Eddin El Faouzi. “Linear and weakly nonlinear stability analyses of cooperative car-following models”. In: *IEEE Transactions on Intelligent Transportation Systems* 15.5 (2014), pp. 2001–2013.

[40] Frank Nielsen and Ke Sun. “Guaranteed bounds on information-theoretic measures of univariate mixtures using piecewise log-sum-exp inequalities”. In: *Entropy* 18.12 (2016), p. 442.

[41] Verena Ziemer, Armin Seyfried, and Andreas Schadschneider. “Congestion dynamics in pedestrian single-file motion”. In: *Traffic and Granular Flow'15*. Springer. 2016, pp. 89–96.

List of Publications

Journal Publications

Publication I: **Subaih, R.**, Tordeux, A., and Chraibi, M. (2024). Comprehensive Review and New Analysis Software for Single-file Pedestrian Experiments. Collective Dynamics, 9, 1–47. DOI: 10.17815/CD.2024.185.

Publication II: **Subaih, R.**, Maree, M., Tordeux, A., and Chraibi, M. (2022). Questioning the anisotropy of pedestrian dynamics: An empirical analysis with artificial neural networks. Applied Sciences, 12(15), 7563. DOI: 10.3390/app12157563.

Publication III: **Subaih, R.**, and Tordeux, A. (2024). Modeling pedestrian single-file movement: Extending the interaction to the follower. Physica A: Statistical Mechanics and its Applications, 633, 129394. DOI: 10.1016/j.physa.2023.129394.

Other Journal Publications

Dias, C., Abdullah, M., Ahmed, D., and **Subaih, R.** (2022). Pedestrians' Microscopic Walking Dynamics in Single-File Movement: The Influence of Gender. Applied Sciences, 12(19), 9714. DOI: 10.3390/app12199714.

Conferences

Poster: **Subaih, R.**, Tordeux, A., and Maree, M. (2023). Single-file Pedestrian Dynamics with Follower Interactions. Pedestrian and evacuation dynamics (PED2023), Eindhoven, Netherlands.

Presentation: **Subaih, R.**, Tordeux, A., and Maree, M. (2021). Quo vadis? Pedestrian Trajectory Prediction in ComplexGeometries. Pedestrian and evacuation dynamics (PED2021), Melbourne, Australia. Link.

GitHub Project

Subaih, R., Chraibi, M., Schrödter, T.: PedestrianDynamics/SingleFileMovement-Analysis: Comprehensive Review of Single-file PedestrianExperiments (2024). DOI: /10.5281/zenodo.10908397.

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