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Editorial: Innovative approaches to pedestrian dynamics: experiments and mathematical models

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Editorial on the Research Topic

[Innovative approaches to pedestrian dynamics: experiments and mathematical models](#)

This Research Topic, *Innovative Approaches to Pedestrian Dynamics: Experiments and Mathematical Models*, brings together contributions that exemplify the current state of research in the study of human and animal mobility, with a focus on bridging theoretical advances, computational techniques, and practical applications. The Research Topic underscores the growing interdisciplinarity of pedestrian dynamics, a field that lies at the crossroads of applied mathematics, physics, engineering, computer science, and behavioral studies. Several contributions expand the repertoire of mathematical models for collective dynamics and deepen our understanding of how temporal and environmental factors modulate collective behavior. For reference, a brief review of previous studies of pedestrian dynamics, in which experimental study is excluded, is summarized in [Table 1](#).

Recent advances in modeling pedestrian and crowd dynamics emphasize the importance of multi-scale and data-driven approaches. Within the present issue, [Horiai et al.](#) have demonstrated that large-scale evacuation scenarios, such as tsunami responses, can be efficiently managed using macroscopic traffic-flow optimization based on zonal macroscopic fundamental diagrams, which help distribute pedestrians across multiple safe routes and alleviate congestion. Complementary to these macroscopic formulations, hybrid models coupling microscopic and mesoscopic descriptions capture how local behavioral factors, such as fear contagion, influence collective motion and evacuation efficiency in heterogeneous environments, c. f., [Perepelitsa and Quaini](#). Statistical and computational approaches by [Stock et al.](#) combining mean-field theory and Monte Carlo simulations have further elucidated the dynamics of multiple interacting species of agents, revealing emergent transitions between Gaussian-like spatial distributions under varying crowd densities.

With the growing availability of real-world data, vision-based pedestrian tracking and social-force inference methods have emerged as valuable tools for connecting theoretical models to observable behaviors, enabling quantitative assessments of interaction forces and trajectory prediction in complex environments, as shown by [Zhu](#). At a broader scale, hydrodynamic models of collective behavior incorporating time delays and obstacle

TABLE 1 Review of studies of pedestrian dynamics.

Category	Summary	Key references
Historical Background/Foundational Theory	Henderson introduced a fluid dynamics analogy using Navier-Stokes-like equations. The Fundamental Diagram (density vs. velocity) became a standard calibration tool	Henderson [1]; Vanumu et al. [2]
Microscopic Model I:Social Force Model	The most fundamental model proposed by Helbing and Molnár. Several refinements exist	Helbing and Molnar [3]; Farina et al. [4]; Johansson et al. [5], Johansson et al. [6], Yu et al. [7]
Microscopic Model II:Heuristic Models	Reject outdated “panic mode” assumptions. Models treat pedestrians as rational agents who avoid collisions or follow peers/leaders	Festa and Wolfram [8]; Lü et al. [9], Zhang et al. [10]; Sieben et al. [11], Moussaïd et al. [12], Degond et al. [13], Degond et al. [14], Bailo et al. [15]
Microscopic Model III:Cellular Automata (CA)	Discretizes space and time using local transition rules. Computationally efficient for large-scale simulations. Improvements include sub-meshes, multi-cell agents, and triangular grids	Feliciani and Nishinari [16], Bazior et al. [17]; Ji et al. [18]
Mesosopic Model I:Kinetic Theory	Helbing’s Boltzmann type equation. Monte Carlo method is used for calculation. Bridges microscopic and macroscopic scales	Helbing [19], Bakhdil et al. [20]; Kim and Quaini [21]; Cristiani et al. [22]
Mesosopic Model II:Electric-Circuit Analogy	Zhong’s model maps pedestrian flow to electrical networks. Roads act as resistors, and people are moving charges. Reduction of mesh complexity	Zhong et al. [23]
Macroscopic Model I:Continuum Dynamics	Hughes’ model combines conservation laws with Eikonal equations. Introduces bounded rationality into fluid-based models	Hughes [24]
Macroscopic Model II:Mean-FieldGame Theory	Combines Hamilton-Jacobi-Bellman and Fokker-Planck equations. Enables modeling of forward-looking decision making under congestion	Lasry and Lions [25], Yano and Kuroda [26]
Physical Analogy:Active Soft Matter	Pedestrians are treated as active soft matter. Phenomena such as jamming, arching, and force-chain transmission appear. Both Faster-Is-Slower and Faster-Is-Faster effects observed in accordance with velocity of pedestrian	Zuriguel et al. [27]; Garcimartín et al. [28]; Al Reda et al. [29], Nicolas et al. [30], Sticco et al. [31]
Applications	Used in urban planning, architecture, and disaster risk management. Agent-based simulations assist evacuation route design	Batty [32], Lämmel et al. [33]
Recent Developments:Integration with AI	AI-based models predict pedestrian trajectories. Techniques include GCN + LSTM forecasting, social attention, reinforcement learning for collision avoidance, and PINNs for equation solving	Zong et al. [34], Mai et al. [35]; Everett et al. [36]; Guo et al. [37]

potentials have provided new insights through the work by Zheng et al. into alignment, obstacle avoidance, and the onset of flocking or dispersal phenomena. Similarly, nonlocal advection systems for competing biological species that include delayed resource recovery offer a biologically grounded framework for studying population coexistence and spatial segregation under realistic constraints, see Zeng et al.. Finally, cross-species analyses by Ishikawa et al. of movement trajectories reveal universal statistical regularities in animal and human mobility, characterized by scaling relationships between enclosed area and trajectory length. These findings suggest a transition from two-dimensional to one-dimensional movement patterns depending on environmental and social constraints, highlighting a unifying geometric principle across taxa.

Collectively, the articles in this issue advance the field of pedestrian dynamics along three interconnected axes: the refinement of theoretical and mathematical foundations, the integration of data-driven and hybrid modeling techniques, and the application of these methods to real-world challenges of safety, efficiency, and resilience. The issue reaffirms the dual identity of pedestrian dynamics as both a fertile ground for exploring fundamental questions of collective behavior and a domain of urgent societal importance.

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Conflict of interest

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Correction note

This article has been corrected with minor changes. These changes do not impact the scientific content of the article.

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