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Scouring Through the Crowd Simulation Dynamics in Urban Environments

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Abstract: In recent years, crowd simulation has gained increasing attention due to its vast potential, especially in architecture, urban planning, and disaster management fields. This involves creating computer-generated models that simulate large groups' movement and behavior. Many simulation approaches, such as microscopic, macroscopic, and mesoscopic models, can be used, each with its advantages and disadvantages. Analyzing the types and categories of crowd simulations provides insight into the evolution of technology. Several studies dealing with urban planning implications were examined to analyze each pedestrian flow model and to synthesize their strengths, weaknesses, and ethical considerations. This review serves as a resource for urban development professionals, AI simulation specialists, and researchers working at the intersection of crowd dynamics and city planning. Overall, this article presents a systematic analysis of crowd simulation literature, elucidating current limitations, future trajectories and research opportunities for enhanced efficiency and realism.

Keywords: *Crowd simulation; Computer graphics; Intelligent Agents; Boids; Pedestrian Crowds; Multi-scale Modelling; Group Dynamics; Real-time simulation; Urban Systems; Resilience.*

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I. INTRODUCTION

Crowd simulation is an approach to understanding, predicting, and reproducing human crowd behavior, which replicates virtual individuals' movement dynamics. The notion of a crowd refers to gathering many people in one place. Human groups, animal herds, insect swarms, and vehicle flows are examples of crowds, which are complex systems that consist of collections of individuals, sharing the same physical environment. They exhibit collective behaviors distinct from individual actions.

One of the earliest approaches to crowd simulation in computer graphics dates to Reynolds' "Boids" system from the 1980s [1]. In recent years, crowd simulation has gained significant attention across various research fields, extending beyond computer animation and simulation. Among its applications are urban planning, military simulation, safety science, entertainment, and sociology. Games, movies, and many other forms of entertainment use realistic computer simulations of human crowds as well as safety and security (e.g., crowd management, and evacuation studies). This multidisciplinary field intersects computer science, graphics, robotics, physics, cognitive science, traffic theory, civil engineering, and mathematics.

In public areas such as terminals, shopping malls, stadiums, and streets, people are exposed to crowded pedestrian movements. A pedestrian flow model can be classified into three categories: microscopic models, macroscopic models, and mesoscopic models. Study objectives and detail level determine the right crowd dynamics model. Research in crowd simulation encompasses experiments for understanding human behavior, algorithms for simulating this behavior, and applications of these algorithms for specific purposes.

Despite notable progress and demonstrated applications in crowd simulation, the field remains rapidly evolving. Complex crowd behaviors driven by physiological, psychological, and social factors present ongoing challenges. Additionally, the computational complexity of modelling heterogeneous crowd limits crowd simulation realism. Given advancements in computer equipment, there is a growing interest in simulating realistic crowds. This is to enhance visual effects, improve virtual reality immersion, optimize urban planning, and facilitate efficient emergency evacuations.

In this article, I examined various aspects of crowd simulations and envisioned how future research directions in crowd simulation will contribute to the development of more effective and realistic applications. This study begins by exploring the concept of the evolution of crowd simulation. Four distinct periods of its development are introduced, followed by an analysis of how each decade's evolution looked within the framework of research approaches developed at that time. Next, the three major

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divisions of crowd simulation are illustrated: microscopic, macroscopic and mesoscopic models, and their sub-categories. This deeper examination opens with a pedestrian flow model explanation and ends with their types. As a next step, crowd simulation models are evaluated and summarized in terms of their strengths and weaknesses, and their potential field applications, risks, ethical considerations, and taxonomical framework. Finally, it is concluded by identifying the remaining challenges and addressing those provides new avenues for crowd simulation as well as more inspiration for further research.

II. CROWD SIMULATION: EVOLUTION OVER THE DECADES

This section presents the historical development of crowd simulation in the form of four periods, illustrating the framework of research approaches taken at that time.

- *From the late 1990s*

Crowd simulation has evolved over many decades, beginning in the 1970s and 1980s. In the late 1990s, crowd simulation techniques and models were developed primarily for use in the entertainment industry, such as animating movies and playing video games.

- One of the first to suggest a distributed model for animating and directing a set of characters was in 1987 [1]. He termed each member called boid. They could easily each sense and react to their surroundings and the other boids on their own. According to Reynolds, a flock is a boid's closest group. To avoid collisions and calculate speeds and directions, these boids in the flock communicate with one another.
- An experimental study by Helbing et al. [2] used physics and socio-psychological factors to develop a model of particle systems, each with a predetermined speed that tends to change with time. This model explains how people behave in crowds during the panic. Interaction forces force particles to maintain a velocity-dependent distance from each other.
- The first technique to model crowds was put forth by Musse and Thalmann in 1997 [3], using a hierarchical control to have the crowd composed of groups and made up of individuals. Additionally, leadership and other sociological factors were mathematically defined to incorporate crowd judgments.
- Using steering behaviors in 1999 [4], Reynolds demonstrated how autonomous characters could move in a natural and improvised manner by demonstrating steering behaviors in animation and video games.

- *From the early 2000s until the late 2000s*

As computer graphics and simulation techniques based on environment and behavior advanced and the field began to diversify in the early 2000s, researchers of this generation focused on modelling individual behaviors with the group, crowd, and environmental structures.

- One such is the ViCrowds concept presented by Musse and Thalmann [5], which suggests that individuals create groups, which then generate crowds. In this situation, users can utilize various sorts of information to govern each level of the hierarchy as they see fit.
- In Anderson's [6], constrained flock animations are generated by creating constrained group animations, which allow users to constrain the location of agents at any point in the animation, or to compel them to remain in a single mass or shape constraint.
- Loscos et al. [7] developed a method in 2003 that allowed 10,000 pedestrians to be simulated in real-time scenarios. The primary goal was to propose a method for simulating pedestrian crowds to improve pedestrian behavior on a local and global scale.
- According to Farenc et al. [8], virtual humans can be replicated in complex environments. The project suggests building an environment that includes rules of behavior that virtual people could use in addition to the environment's geometric representations.
- To enable quick pathfinding and effective navigation for virtual humans evolving inside a crowd, Lamarche and Donikian [9] developed a navigation algorithm.
- It's interesting to note that few researchers offered data-driven approaches to crowd simulation in the late 2000s.
- According to Musse et al. [10], their approach is a computer vision-based method for simulating crowds.
- Currently, microscopic models, such as psychological models, are incorporated into crowd simulations. Among the suggestions made by Pelechano et al. [11] is to incorporate psychological roles, communication, and modelling into crowd simulation. As well as creating crowd models, they created leaders who could influence the agents in the model.
- In "Continuum Crowds" [12], macroscopic modelling is also used to model massive crowds without explicitly avoiding a collision. To do so, it presents a dynamic potential field which blends barriers that are continually moving with global navigation.

➢ *From the early 2010s until the late 2010s*

The need for more independent as well as intelligent agents became apparent in the late 2000s. Thus, the early 2010s phase was particularly rich in terms of fresh perspectives and ideas, and some significant navigation and collision avoidance algorithms were pushed forth during this time.

- The well-known Optimal Reciprocal Collision Avoidance (ORCA) approach has become a staple in crowd domain benchmarks since its initial proposal in 2011 [13].
- According to Bicho et al. [14], BioCrowds is the first crowd-based algorithm free of collisions. Using a space subdivision strategy, agents compete for available space and only move when there is sufficient room.
- Based on data collected from real-world crowd movement, Wolinski et al. [15] provided a methodology for assessing multi-agent crowd simulation techniques.
- Moreover, SteerPlex was developed by Berseth et al. to quantify crowd simulation complexity [16], with SteerFit serving as its extension and aiming to present automatic parameter fitting for steering algorithms [17].

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When technological advancements, particularly in the fields of artificial intelligence, machine learning, and big data, allow for more sophisticated and precise analysis and simulation of crowd behavior, it can be said that the current state of the art in crowd stimulation began to take shape in the early 2010s with an influx of new ideas. Although AI techniques like deep learning and reinforcement learning were first established in the late 2000s, the early 2010s gave momentum to their development and allowed researchers to start using them to build more complicated models of crowd behavior. Since the late 2010s, there has been a noticeable rise in the application of data-driven technologies, such as deep learning and reinforcement learning, including machine learning and statistical prediction techniques.

- In the late 2010s, computer vision [18], natural language processing, and speech recognition began to use deep learning extensively. Deep learning is a subset of machine learning that uses multi-layered neural networks to retrieve features and patterns from datasets. To interpret crowd behavior, researchers started applying deep learning algorithms to examine social media data, such as texts and images. Regression neural networks (NN) are used by Liu et al.[19] to forecast the aggregate attributes of crowd dynamics.
- A data-driven strategy for simulating crowds that may imitate the observed traffic of pedestrians in a certain location was presented by Amirian et al. [20] and trained using generative adversarial networks (GANs).
- Furthermore, Testa et al. [21] present an innovative method for estimating complex environment evacuation times with a 5% error rate compared to real-life scenes. ANNs are developed by the authors for mastering evacuation times for rooms of different sizes, using per-room data to estimate the whole environment accurately.
- The use of reinforcement learning, a type of machine learning where agents learn from their environment by engaging with it, in the field of crowd stimulation began to surface in the late 2010s. As a result, it was feasible to predict crowd behavior in various circumstances and to create simulations of crowd behavior that were more realistic. Ravichandran et al. [22] developed a model where pedestrians were represented as autonomous and proactive learning agents. They employed reinforcement learning (RL) to ease continuous learning and adaptation in pedestrians' behavior.
- The study went as far as to explore interactive experiences, virtual reality, and manipulating agent emotion. For instance, Borg et al. [23] proposed extending Bosse's approach [24] explicitly to the domain of crowds. The authors' work proposes spreading emotion among crowd agents.
- Using parameters taken from real-world videos, Basak et al. [25] suggest a data-driven method for fine-tuning crowd simulation.
- A study by Latoschik et al. [26] suggests examining user interaction and performance in Social Virtual Reality (SVR), which offers face-to-face interaction. Immersive interaction was found to help the user study.

➢ *From the early 2020s and beyond*

As technology advanced in the early 2020s, crowd simulation fundamentally transformed, expanding beyond traditional applications in transportation, urban planning, and disaster management to incorporate autonomous vehicle systems, unmanned aerial vehicles, and social media analysis in accordance with human social norms. Across both physical and virtual environments, these convergences have revolutionized methodologies for analysing, predicting, and managing crowd dynamics.

- A few strategies have already been put up for 2021 to help with crowd management during COVID-19 and other cases concerning building evacuations, hazardous events like terrorist attacks, methods for finding the best route, and even the influence of groups of agents on crowd efficiency. Here are a few instances: Based on Dijkstra's well-known algorithm [27], Mirahadi and McCabe [28] provide a working model for generating evacuation scenarios.
- Microscopic models like the Social Force Model (SFM) and cellular automata are often used. For example, Shi et al. study [29] employs the software called Viswalk to simulate the effects of evacuation flow in emergency and normal scenarios using the SFM (Social Force Model). Using an extended cellular automata framework, Li et al. [30] investigate paediatric hospital evacuation in a rule-based model that considers agent grouping.
- As social media platforms have grown in popularity, this field has shifted to understanding and forecasting crowd behavior. Thus, the field began to diversify into new areas like online communities, social networks, and virtual worlds. In an article by Alasmari et al. [31], they illustrate how deep learning applications can be used to analyze social media during the Hajj pilgrimage to predict and manage crowd behavior.

It's noteworthy that crowd simulation is a multidisciplinary field that pulls on a broad range of disciplines, including computer science, engineering, physics, psychology, and sociology. This diversity of ideas and methodologies is one of its strengths, allowing it to adapt and for new trends to arise. The synergy between human behavior understanding and technological advancement continues to drive innovations in crowd simulation and management, preparing cities for the challenges of an increasingly automated future.

III. CLASSIFICATONS OF CROWD SIMULATION MODELS

A systematic overview of crowd simulation models is presented in this section, which discusses microscopic, macroscopic, and mesoscopic, along with their respective subcategories, as shown in Fig 1. A pedestrian flow model is examined as a framework for understanding the sub-categories of microscopic and macroscopic models. A comprehensive comparison of these modeling techniques, highlighting their key differences, is provided to grasp their unique characteristics and applicability. Afterwards, the subcategories of mesoscopic models - dynamic group behavior, interactive crowd formation, and social psychological factors - are explored in greater detail, as they

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bridge the gap between microscopic and macroscopic approaches by combining individual-level interactions with flow-based crowd dynamics.

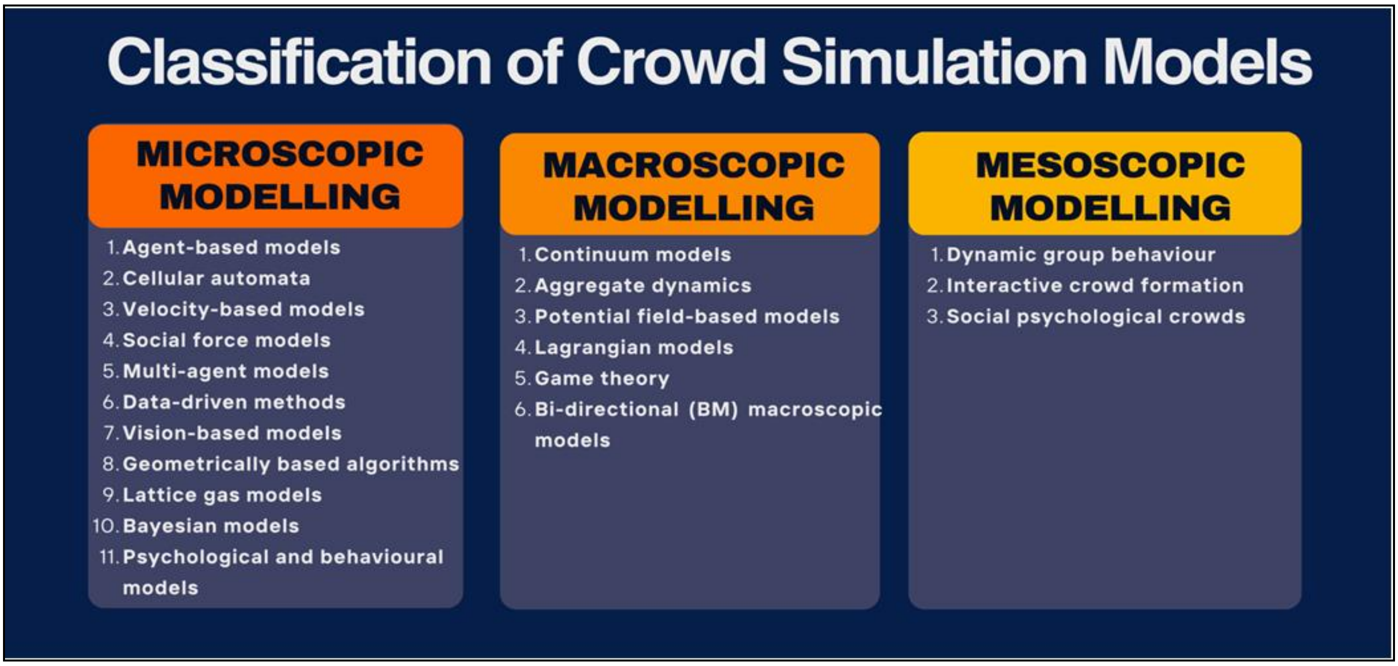

Fig 1 Crowd Simulation Models: Microscopic, M acroscopic, and Mesoscopic Approaches with Their Sub-categories.

➢ *Microscopic crowd simulation modelling*

Microscopic simulation models, or "Bottom-Up" models, capture intricate details about individual behavior. Individuals are considered discrete entities whose movements are influenced by their surroundings and obstacles. Combining local behaviors, including collision avoidance, shapes overall movement.

Within microscopic crowd simulations, each person is represented as an agent with unique properties such as size and walking speed. In addition, each person has motivations like a goal position. This bottom-up approach links individual behavior to crowd behavior. In each simulation step, agents update their velocity by considering neighboring agents and obstacles, following specific rules that govern their local behavior.

A variety of microscopic models have been developed to accurately predict crowd motion and interpret self-organized phenomena. These models include agent-based models, cellular automata, velocity-based models, social force models, multi-agent models, data-driven methods, vision-based models, geometrically based algorithms, lattice gas models, Bayesian models, psychological models, and behavioral models. Some surveyed studies explore the integration of two microscopic models to enhance the simulation's accuracy and realism, using the strengths and capabilities of each model.

➢ *Microscopic pedestrian flow model*

In the domain of microscopic crowd simulation, researchers often simplify the crowd's movement environment to a two-dimensional plane with polygonal obstacles. The individuals within the crowd are typically represented as disk-shaped particles, and all measurements are standardised in meters. This entails a collection of 'm' non-overlapping obstacles, denoted as Equation (1), where each obstacle O_i is a simple 2D polygon. Furthermore, the simulation incorporates a group of 'n' agents, denoted Equation (2), with each agent modelled as a disk of radius r_j. Each agent A_j is assigned a preferred walking speed $s_{pref,j}$, expressed in meters per second, which remains constant throughout the simulation.

$$OBS = \{O_i\}_{i=0}^{m-1} \qquad (1)$$

$$AG = \{A_j\}_{j=0}^{n-1} \qquad (2)$$

The position of agent A_j at a given moment is represented by p_j, while its velocity is represented by v_j. In each step of the simulation, the focus is on updating the velocity v_j of each agent, allowing them to navigate effectively while avoiding collisions. Each agent aims to achieve a preferred velocity, v_{pref}, which may be driven by reaching a specific destination or following a designated route.

In a microscopic crowd simulation, the simulation progresses in discrete time steps, typically representing 0.1 seconds per frame. During each frame, every agent A_j goes through the following steps:

- Neighbour search: Agents identify nearby agents and obstacles within a certain range, gathering information. This range can be a disk with a predetermined radius or a viewing angle.
- Preferred velocity: Agents calculate a preferred velocity (v_{pref}), based on the environment's geometry, considering their goal and potential obstacles. This preferred velocity can be a straight path to the goal or a

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predetermined global path around obstacles. The calculation depends on whether global path planning is used.

- Local navigation: Using both sets of information, each agent computes a new velocity (v_{new}) or acceleration to meet certain criteria, such as avoiding collisions with neighbours and staying close to the social group.
- Movement: Agents update their position based on the new velocity or acceleration, using a common Euler integration method.

By following these steps, the microscopic crowd simulation ensures that agents navigate effectively, considering their surroundings and interacting with neighbouring agents while avoiding collisions.

➢ *Microscopic pedestrian flow model*

After explaining the fundamental concepts of microscopic crowd simulation modelling, it's crucial to understand the distinct characteristics of various microscopic models from surveyed papers.

➢ *Agent-based modelling:*

Agent-based microscopic modelling is a powerful technique used in crowd simulation to examine the behaviour of individuals within a crowd. This method involves the creation of autonomous entities called agents, which represent individuals in the crowd. Agents have distinct characteristics, behaviours, and decision-making processes [29]. They interact with each other and the environment, such as physical obstacles, landmarks, and fellow agents. A variety of techniques are used to model each agent's behaviour, such as rule-oriented models, decision trees, and machine learning algorithms. Modelling approaches consider an agent's personality, goals, preferences, and beliefs. By using real-time information, agents can make dynamic decisions and adapt their behaviour based on available data. Due to this adaptability, crowd behaviour can be simulated more realistically as agents respond to changing conditions. To ensure scalability and effectively simulate complex human behaviours at both local and global levels, agent-based models can be combined with path planning or macroscopic models.

Crowd-related phenomena, such as pedestrian dynamics, evacuation scenarios, and crowd behaviour in public spaces, studied using agent-based microscopic modelling. Besides that, it can be used to test different scenarios and interventions to determine whether crowd-management strategies work in diverse settings. It is a versatile tool in emergency management, urban planning, and safety engineering.

➢ *Cellular automata*

A cellular automata microscopic model can be used to analyse individual behaviour in a crowd through crowd simulation. Individuals' movements are represented using a grid of cells in a given space [32]. Each cell corresponds to a specific area of the environment. This modelling approach divides the environment into multiple cells, each adopting various states. Rules dictate how each cell's state changes in time as changes within the environment occur. These rules consider the presence of other agents, obstacles, destinations, preferred speed and landmarks, as well as neighbouring cells' behaviour. Crowds are represented by particles or agents that move between adjacent cells. The surrounding cells determine how these agents move.

Cellular automata models are used for pedestrian flow, congestion, evacuation scenarios, and crowd behaviour to capture emerging phenomena. This is where intricate patterns or behaviours emerge from interactions between individual agents and their environment. In addition to exploring the underlying mechanisms, these models also examine environmental factors and agent behaviours. In conclusion, it is a potent tool for crowd behaviour study. It has significant potential in diverse fields such as urban planning, safety engineering, and emergency management.

➢ *Velocity-Based Modelling*

Velocity-based models run on the principle of allowing each agent to actively decide its next velocity. The velocity stands for the speed and direction of the agent's movement. Agents evaluate multiple velocity options based on specific criteria, such as collision avoidance, to select the most proper choice. This approach fundamentally alters the way agents interact with their neighbours, enabling trajectory adjustments depending on expected outcomes. Despite their higher computational complexity, velocity-driven methods produce superior outcomes and are more representative of human behaviour.

The University of North Carolina research group has made notable contributions to the field with widely used velocity-based collision avoidance models, including Velocity Obstacle (VO) [33] (as shown in Fig 2.a), Reciprocal Velocity Obstacle (RVO) [34] (as shown in Fig 2.b), Optimal Reciprocal Collision Avoidance (ORCA) [35] (as shown in Fig 2.c), and Hybrid Reciprocal Velocity Obstacle (HRVO) [36] (as shown in Fig 2.d). These models use neighbour information for decision-making, resulting in a collective movement of individuals driven by local interactions, without the need for explicit environment representation using techniques like grid division.

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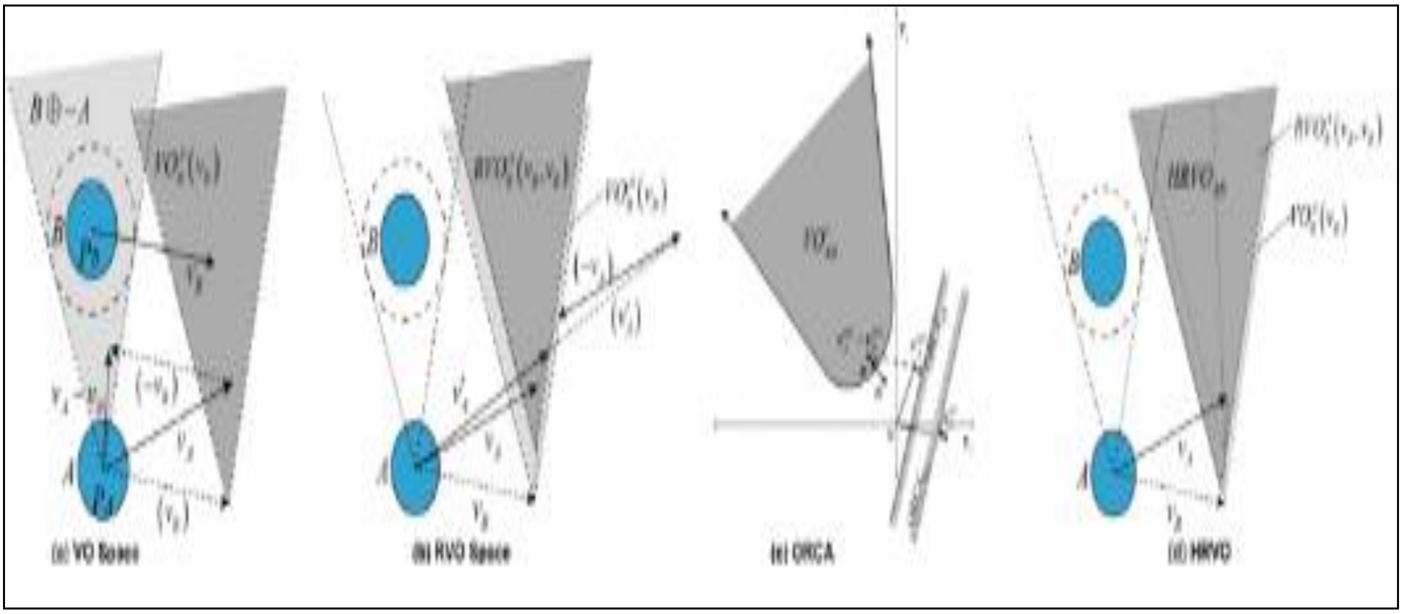

Fig 2 Diverse velocity barriers.

➢ *Social force modelling*

In 2000, Helbing et al. introduced the Social Force Model (SFM) [37] as a framework for analysing crowd panic dynamics during escape scenarios. Drawing inspiration from interaction forces, it has become a prominent and widely used approach to simulating human behaviours. Its introduction was a significant milestone in microscopic human crowd simulation, as it incorporated physical criteria, influencing subsequent research efforts. Within SFM, individual behaviours are influenced by socio-psychological and physical forces. Factors such as desired target direction, velocity, and interactions with the environment decide individuals' actual movement.

In Equation (3), the acceleration [37] of an individual denoted by i, influenced by various components, reflects the interplay of different forces. These components include the desired walking speed (v_i^0), mass (m_i), target direction (e_i^0), current velocity (v_i), interaction forces with other individuals (f_{ij}), and forces exerted by walls (f_{iW}). Fig 3 illustrates the update time-step (τ_i) within the model. Within this framework, each agent is represented as a particle and meets two primary types of forces: an attractive force guiding them towards the goal position and repulsive forces arising from obstacles and other agents.

$$m_i \frac{dv_i}{dt} = m_i \left\{ \frac{v_i^0(t)e_i^0(t) - v_i(t)}{\tau_i} \right\} + \sum_{j(\neq i)} f_{ij} + \sum_{W} f_{iw} \quad (3)$$

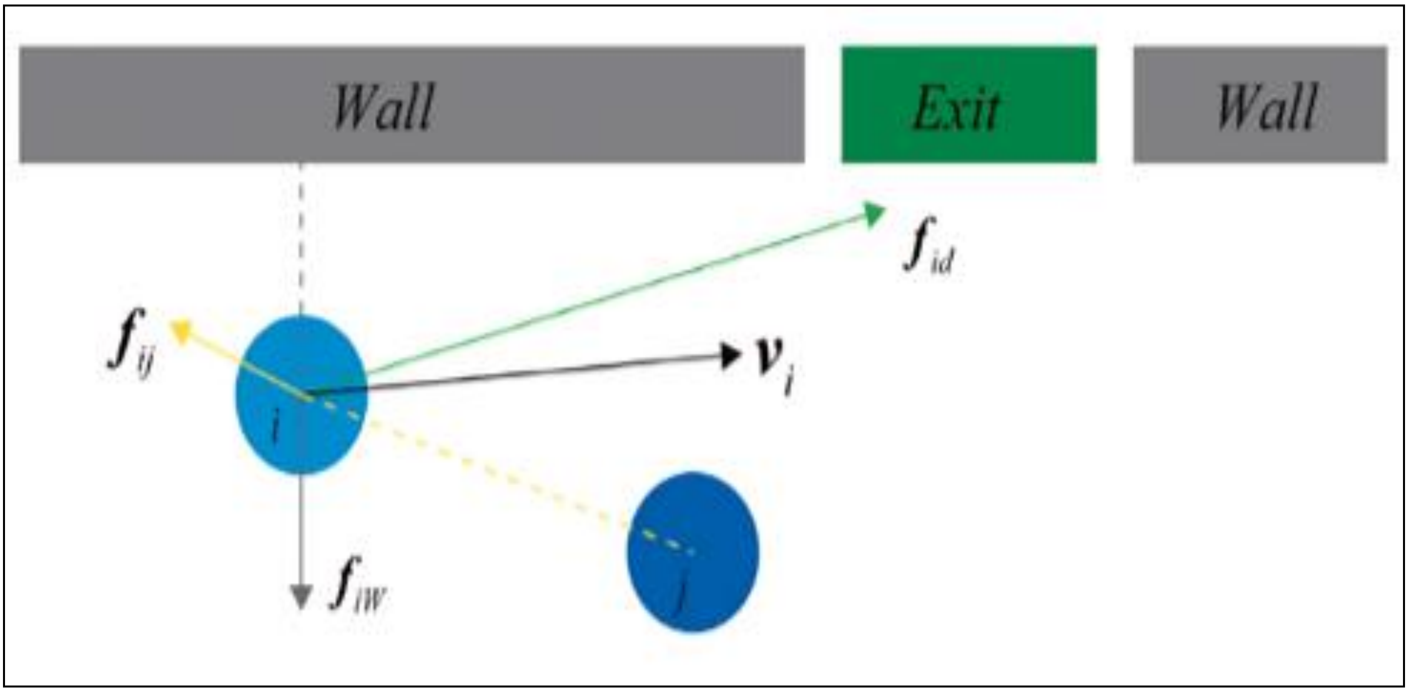

Fig 3 Visualization of the Social Force Model [37].

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The Social Force Model presents an easily implementable concept that works effectively for numerous applications. It also offers intuitive extensibility by introducing new forces to accommodate added agent behaviors.

- *Multi agent modelling*

The MAM (Multi-Agent Model) system [38] is built upon the intricate interplay between agents and their surrounding environment. Environments can take the form of continuous, discrete, or virtual spaces, while agents can be categorized as cognitive, active, or passive. This dynamic interaction produces a range of influential forces, including repulsion, resistance, randomness, and gradients. These forces affect pedestrian movement within the environment. Gaining insights into these local interactions is crucial for the development of correct prediction models, such as MAM, which aim to effectively simulate crowd dynamics. Furthermore, crowd motion dynamics emerge from the interconnectedness between pedestrians and their environment. It is worth noting that in dense pedestrian flows, spontaneous unidirectional lanes are common. However, as density increases, the smooth flow may deteriorate, resulting in phenomena like stop-and-go movements and crowd turbulence waves.

The extensive application of the MAM technique [38] in various scenarios highlights its position as a preferred methodological approach for analyzing and predicting heterogeneous human behaviors. Offering distinct advantages over computer technology, MAM provides a robust platform for simulating autonomous interactions between multiple intelligent agents. It surpasses agent-based modelling (ABM) in terms of its ability to conduct more sophisticated and detailed studies, solidifying its position as an advanced framework in the field.

- *Data-Driven Methods*

Rooted in input data, typically including trajectories derived from real human crowds, data-driven methods in crowd simulation aim to emulate this input data more abstractly. By avoiding the explicit definition of behavioral rules, these approaches can generate specific and nuanced behaviors that are challenging to capture using simple rules. One of the advantages of data-driven crowd simulation is the inherent adaptability of the models. They automatically adjust their behavior in response to changes in the input data without explicit knowledge of specific behavioral differences. This adaptability adds another layer of flexibility and realism to the simulation process.

Research in this field predates 2010, although early models could not guarantee collision avoidance among agents. However, advancements made in the 2010s, partially attributed to deep learning progress, have been dedicated to mitigating these issues. Crowd motion databases without sufficient adaptation are a common challenge in many methods. However, a recent approach aims to address this problem by leveraging the generalization capabilities of deep learning (DL) [39]. This approach involves acquiring an abstract model of agent behavior through DL, which can be applied to novel scenarios. By utilizing this learned behavioral model, the need for runtime database searching is eliminated, as the agent's actions are determined based on the acquired knowledge.

Data-driven DL technique, Recurrent Neural Networks (RNNs), has proven highly beneficial for local navigation tasks. These networks can learn and predict future states based on recent observations. In our specific case, RNNs are employed to estimate agents' next positions by considering both their neighbors and past motion. While RNN-based models are commonly used in computer vision applications such as tracking or human trajectory prediction (HTP), they can also be effectively employed in crowd simulation scenarios. Once trained, an RNN can serve as a reliable agent-navigation model, enabling efficient and real-time navigation for multiple agents within the simulation.

The Generative Adversarial Network (GAN) is recognized for its remarkable capability to generate diverse outcomes, effectively standing for a probability distribution of possible results. Typically, a GAN includes two crucial components: a generator, responsible for producing new data based on input data, and a discriminator, which differentiates between real and fake data. Both components heavily rely on neural networks, particularly Long-Short-Term Memory (LSTM) networks in the context. During the training phase, the generator and discriminator engage in a competitive process, each striving to outperform the other. This adversarial setup aims to improve the generator's ability to generate outputs that closely resemble real data. In comparison to approaches that solely rely on LSTMs, employing GANs offers the advantage of generating a wider range of trajectories using the same input data. However, it's critical to note that training GANs can be a time-consuming and challenging task, requiring careful control and management.

Reinforcement learning (RL) is a method that involves system learning through iterative trial and error to accomplish a specific objective [40]. It includes a state description, which stands for the agent's current situation. In addition, RL includes a reward function that offers incentives or penalties based on actions leading to state changes. By studying the accumulation of rewards, the system learns the most favorable short-term actions for achieving long-term goals. RL is often applied to tasks with clearly defined goals, such as reaching a target position or winning a game, where reference data may be unavailable.

Leveraging deep neural networks (DNNs), deep reinforcement learning simplifies modelling. With this approach, the state description can be represented by raw data, such as neighboring entities' relative positions and velocities. This is instead of a custom summary. Although a manually defined reward function is still necessary, the trained DNN can assess the desirability of potential actions in a given state. This streamlines the decision-making process. By utilizing DNNs, deep reinforcement learning enhances the efficiency and effectiveness of evaluating actions based on raw data inputs.

- *Vision-Based Modelling*

Vision-based navigation algorithms replicate humans' navigation based on visual input rather than relying on

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complete knowledge of agents' positions and speeds. These algorithms specifically focus on using visual perception to guide locomotion, simulating human-like navigation behavior in their approach.

A research study [41] introduced a synthetic crowd-controlling model based on vision and aims to improve perception-action loop simulation. This model is a variation of existing velocity-based models and offers enhanced capabilities. It achieves individual movement calculations by assessing the bearing angle (α) and time-to-collision (tti) for each pixel. The proposed approach includes adjusting rotational movement based on the derivative of the bearing angle and ensuring collision avoidance through the computation of time-to-interaction. These concepts are visually depicted in Fig 4. In this model, the virtual camera captures environmental information, and each pixel of the resulting image has valuable velocity control data. By incorporating such details, this vision-based model enables more precise and realistic crowd control simulations.

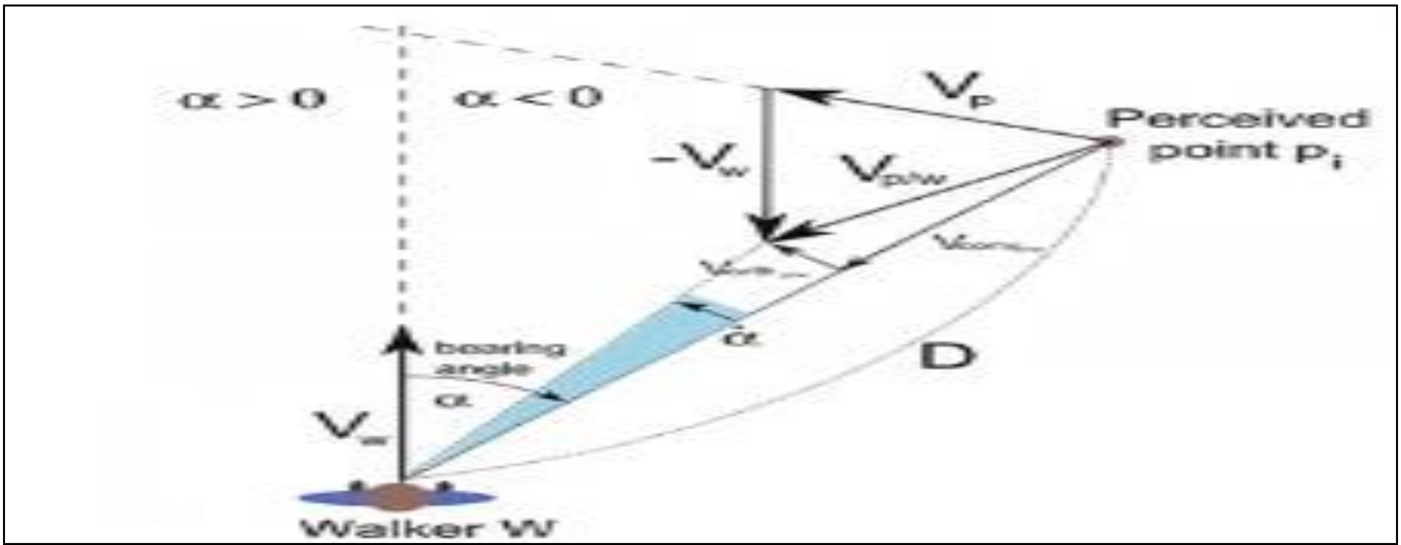

Fig 4 Synthetic Vision [41].

The visually driven steering approach, which falls under the vision-based category of methods, was pioneered by Warren et al. [42], a group of psychologists and researchers. This approach, established before 2010, focuses on modelling behaviour that closely resembles how individuals perceive their environment visually. Instead of relying on precise world coordinates, it considers variables such as object movement within their field of view. Warren et al.'s groundbreaking work also introduced collision prediction techniques based on the bearing angle, integrating empirical experiments with modelling to enhance understanding in this field.

The second category of approaches, known as retina-based steering, takes visually driven steering to the next level by introducing the concept of a virtual retina. Inspired by the human eye, agents in this category are equipped with a synthetic vision that closely resembles human visual perception. Instead of using simplified representations, these methods render a graphical representation of the agent's field of view onto a virtual retina. Within retina-based steering, agents behave based on the pixel information present in their virtual retina. Interactions with other agents or objects are abstracted into interactions with a matrix of pixels, allowing for a more detailed and nuanced representation. The specific rendering techniques employed and the utilization of this information for agent steering can vary among different methods within this category. While retina-based algorithms require more computational resources than velocity-based or force-based algorithms, they aim to provide a more accurate representation of human perception. These methods are typically designed for low to medium crowd densities to ensure manageable performance. They find practical applications in navigation for robots equipped with cameras.

➢ *Geometrically Based Algorithms*

Algorithms based on geometric concepts are widely used in crowd simulations as microscopic modelling techniques. With mathematical models, they can simulate individuals' motion in a crowd utilizing geometric principles. Algorithms like these represent the environment with geometric shapes such as circles, rectangles, and polygons [43]. Spatial boundaries are established by these shapes and obstacles and landmarks can be identified by them. In the crowd, individuals are displayed as point particles or shapes like circles and ellipses. The mathematical model governs motion by integrating variables such as position, velocity, and interaction.

In geometrically based algorithms, mathematical models describe the forces that attract and repel individuals and objects. Microscopically, they enable a deeper understanding of agent dynamics and behaviour, including emergency decision-making. An example would be a hyperbolic-elliptic equation that models individual and collective movements in crowds with finite evacuation periods.

➢ *Lattice gas modelling*

A lattice gas model is used to simulate crowds microscopically. Using a grid-like lattice structure, it simulates individual movement within crowds. Simulation

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space is represented by discrete grid points corresponding to specific locations within the environment. Individuals in this approach are described as particles that move between lattice points to navigate through simulated space [44]. The particle's movement is determined by a set of rules that take neighbouring lattice points and their state into account. It uses transition probability to determine particle movement direction. Particle position and neighbouring lattice points play a role in this. To calculate this probability, weights are assigned to each possible move a particle might make. Researchers can examine crowd behaviour in greater detail and realism with the lattice gas model by simulating individual-level movement within a crowd. This methodology can be used to study pedestrian flow, congestion, evacuation scenarios, and public behaviour. It serves as a valuable tool for investigating individual behaviour in a crowd.

➢ *Bayesian Modelling*

Bayesian models are used in crowd simulation to represent and predict individual agent behaviour microscopically. Using probability distributions, it represents uncertainty and variability in agent behaviour. This model integrates prior knowledge with observed data using Bayesian methods [45]. Human behaviour patterns, social norms, and other relevant factors constitute prior knowledge. Bayesian inference refines and updates predictions using prior knowledge and observed data during the simulation. Due to this, the model generates probabilistic predictions and adapts its estimates based on those predictions. Simulations are more realistic and diverse because Bayesian inference captures inherent uncertainty in agent behaviour. Continuously updating estimates with updated information facilitates dynamic and adaptable predictions. Furthermore, Bayesian models are useful for simulating crowd management, evacuation planning, and urban design in real-world situations, as they produce precise and nuanced simulations.

➢ *Psychological and Behavioural Modelling*

- Psychological models: It captures the cognitive processes and decision-making mechanisms of agents in a crowd simulation. Various psychological factors are considered, such as learning, attention, perception, and memory. Cognitive psychology theories may be incorporated into these models to simulate realistic thinking and behaviour. Possibly, they could model how agents perceive and interpret their environments. Its decisions may also be based on beliefs, goals, and lessons learned from the past. This model generates behaviour aligned with human cognitive processes by incorporating psychological factors.
- Emotional appeal models: These describe how emotions influence an agent's behaviour. In these models, emotions are central to decision-making, motivation, and social interaction. Within a crowd simulation, they aim to emulate emotions such as anger, fear, happiness, and empathy. An agent's emotional state can significantly affect its reactions, actions, and social behaviour. When experiencing fear, an agent may change its movement pattern, seek safety, or behave more cautiously. A model incorporating emotional appeal impacts individual and collective behaviour in a more nuanced and realistic manner
- Behavioural-based models: Individual agents' behaviour is influenced by a variety of behavioural factors in behaviour-based models. A variety of disciplines are often drawn upon, including sociology, psychology, anthropology, and economics. Models such as these capture social norms, cultural influences, personality traits, and group dynamics among many other relevant aspects of behaviour. For example, they might simulate how social conformity, national identity, or leadership influence an agent's behaviour. The behavioural-based model attempts to capture the rich complexity of human behaviour through the interaction of various factors.

While there may be overlaps and interconnections between these models, they differ in terms of their primary focus and the specific aspects of individual behaviour they emphasize [46]. In psychological models, a variety of psychological factors are considered, while emotional appeal models emphasize emotions, and behavioural-based models take a comprehensive approach by considering various behavioural influences.

➢ *Macroscopic crowd Simulation modelling*

As evidenced by previous research, crowd dynamics at a macroscopic level are forged by interactions between individuals at a microscopic level. Flow, density, and velocity are all incorporated into these models to accurately predict large-scale crowd dynamics. Since they replicate observed self-organizing phenomena, they are useful for applications such as simulation, real-time estimation, and crowd management. Traffic theory uses the term "macroscopic" to describe abstract models that study density and flow rather than simulating traffic.

Macroscopic models simulate crowd motion using vector fields, describing velocity distributions based on mass conservation. Lagrangian and Eulerian approaches are employed for dense crowds with minimal individual variation. These models utilize partial differential equations, drawing from fluid dynamics to describe crowd density changes over time. Applications include simulating stadiums, shopping malls, and subways with large crowds. However, numerical methods face limitations, particularly in accurately determining traffic states and handling complex geometries, requiring re-mesh techniques and grid generation that can introduce complexity and information loss. Various macroscopic models, including continuum models, aggregate dynamics, potential field-based models, Lagrangian models, game theory, and bi-directional (BM) macroscopic models, have been developed to study crowd motion.

➢ *Macroscopic pedestrian flow model*

The macroscopic model examines the movement of many pedestrians within a two-dimensional continuous walking facility. It focuses on satisfying the mass conservation equation, which ensures a consistent pedestrian flow throughout the space. In this model, the equation is expressed in Lagrangian form, utilising a coordinate system that moves with individual pedestrians.

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This differs from the Eulerian approach, which uses a fixed coordinate system in space.

➢ *The key Equations in this Model are:*

- *Density Equation*: $\frac{D\rho}{Dt} = -\rho(\nabla \cdot \vec{v})$ (4)

- This Equation (4) helps us understand how the density of pedestrian changes over time. The equation relates time (t) to the pedestrian density (ρ) at any given point in the facility. It considers the position vector ($\vec{x}$) and velocity vector ($\vec{v}$) of the pedestrians, allowing for the analysis of their movement. Then *Dt* represents the change in time, and *D/Dt* represents the derivative concerning the moving coordinate system.

- *Acceleration Equation*: $\frac{D\vec{v}}{Dt} = \vec{\epsilon} - \frac{1}{\rho}\nabla \mathrm{P} + \vec{E}$ (5)

- This Equation (5) helps us understand how their velocity changes over time. This equation determines the acceleration of the pedestrian flow, considering both internal factors such as Pressure (P) and external forces ($\vec{E}$) such as interactions with wall boundaries.

To guide pedestrians towards their destination, the navigation term ($\vec{\epsilon}$) adjusts the velocity of each pedestrian based on their desired equilibrium velocity. The equilibrium velocity depends on the local density (ρ) and the relative position of the point ($\vec{x}$) to the destination. Pressure (P) is defined as the psychological discomfort caused by proximity to other pedestrians. It increases with density, steering pedestrians towards less crowded areas. The pressure term complements the navigation term by considering local path choices. The additional term ($\vec{E}$) in the equation introduces behavioural assumptions specific to certain applications. Different assumptions result in different models of pedestrian flow. It's important to note that the speed of pedestrian flows is limited by the physical capabilities of individuals.

Overall, the equation combines navigation, pressure, and additional factors to model pedestrian behaviour and ensure numerical stability. By utilizing these equations, the macroscopic model provides insights into the collective behaviour of pedestrians in the walking facility, without focusing on individual pedestrian movements.

➢ *Macroscopic Model Types*

After exploring the fundamental concepts of macroscopic crowd simulation modelling, it's important to understand how different models from various research papers approach the field. While all these models share basic pedestrian flow principles, their approaches vary significantly.

➢ *Continuum Modelling*

The notion of continuum theory, proposed by Hughes, provides a systematic framework for characterizing pedestrian flow dynamics. By assuming certain properties of pedestrians, it becomes possible to solve flow equations that can be applied to model the behaviors of individuals within a crowd.

Expanding upon Hughes' theory, Treuille et al. introduced a real-time, large-scale crowd simulation method known as "Continuum Crowds" [12]. This pioneering approach is the first instance of a macroscopic model developed specifically for simulating large-scale crowd scenarios.

The application of continuum crowds leads to the derivation of dynamic potential fields, including speed fields, density fields, and discomfort fields [12]. These fields offer valuable insights into crowd behavior. Moreover, the overall unit cost function for a group of individuals is computed using Equation (6):

$$\int_P C\,ds, \quad where \quad C \equiv \frac{\alpha f + \beta + \gamma g}{f} \qquad (6)$$

In Equation (6), each term in the numerator corresponds to an integral that considers factors such as individual distance length, time of travel, and crowd density. The weights α, β, and γ determine the relative importance of these terms in the calculation. This cost function plays a critical role in characterizing crowd behavior and interactions.

The algorithm flow, as shown in Fig 5.a, utilizes the Eikonal equation [12] to calculate the optimal path planning, represented by Equation (7):

$$\|\phi(\boldsymbol{x})\| = C \qquad (7)$$

The cost function C is measured by the direction of the gradient, where individuals move in the opposite path of this gradient. This approach generates interesting moving patterns such as vortex formation and lane formation. Additionally, it is capable of simulating large-scale army retreating, as showed in Fig 5.b.

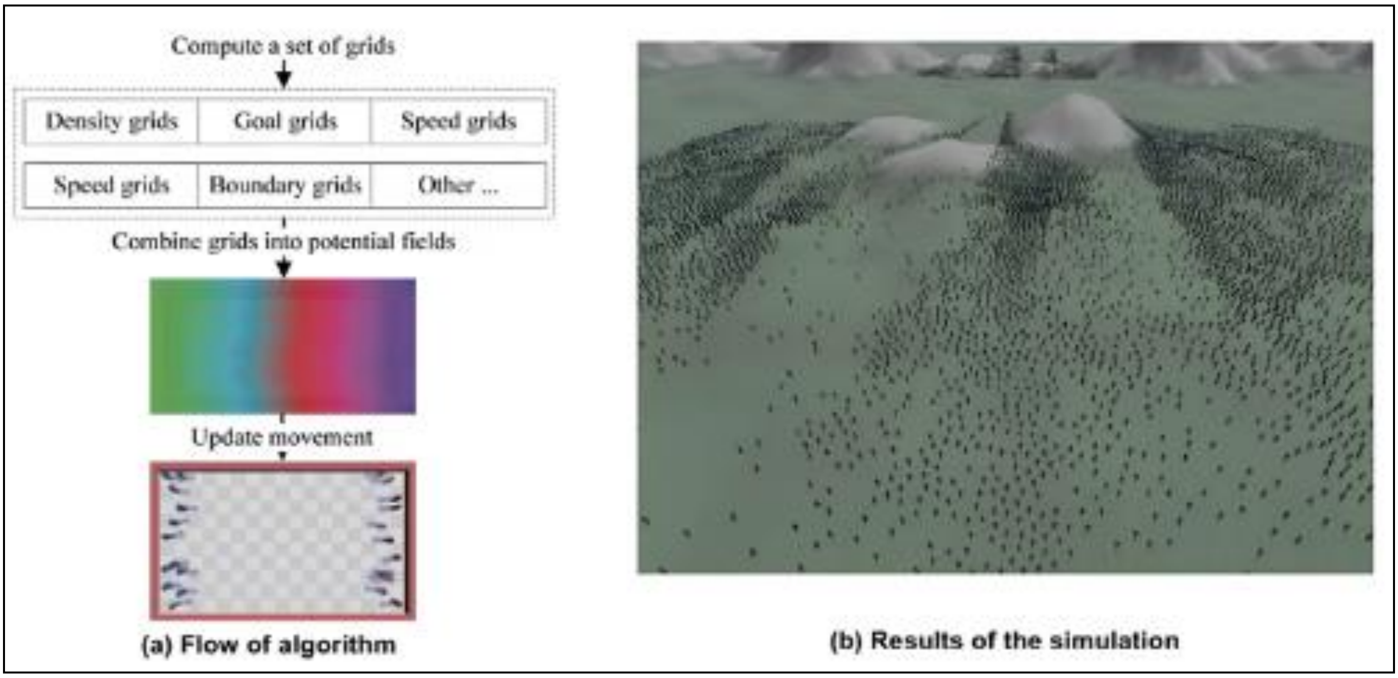

Fig 5 The Complete Sequence of the Continuum Crowd's Algorithm [12].

➢ *Aggregate dynamics*

The concept of the aggregate dynamic model draws inspiration from fluid dynamics. By employing a dual representation [68], the crowd compressibility is assessed using both discrete agent-based modelling and a unified continuous system. This novel approach, known as "UIC," enables the simulation of large crowds comprising hundreds of thousands of individuals in real-time, as depicted in Fig 6.a.

Within the aggregate dynamic system, the UIC projection embodies a constrained continuum model. This model sets up a relationship between the agent's velocity field and density field [47], as specified by Equation (8):

$$\frac{\partial\rho}{\partial t} + \nabla\cdot(\rho v) = 0 \quad (8)$$

To uphold the UIC constraints, a correction of $\tilde{v}$ and ρ is necessary [47], as detailed in Equation (9):

$$v = v_{\max}\frac{\tilde{v}-\nabla\rho}{\|\tilde{v}-\nabla\rho\|} \quad (9)$$

At the start of the simulation, each agent is assigned a preferred velocity, resulting in varying velocity and density fields. By decoupling local collision avoidance, the UIC projection enables the generation of high-scale crowd simulations at near-interactive rates on desktop computers, as illustrated in Fig 6.b. Future work involves exploring how UIC projection could enhance simulations involving diverse types of interactions, such as simulation or crowd control robots.

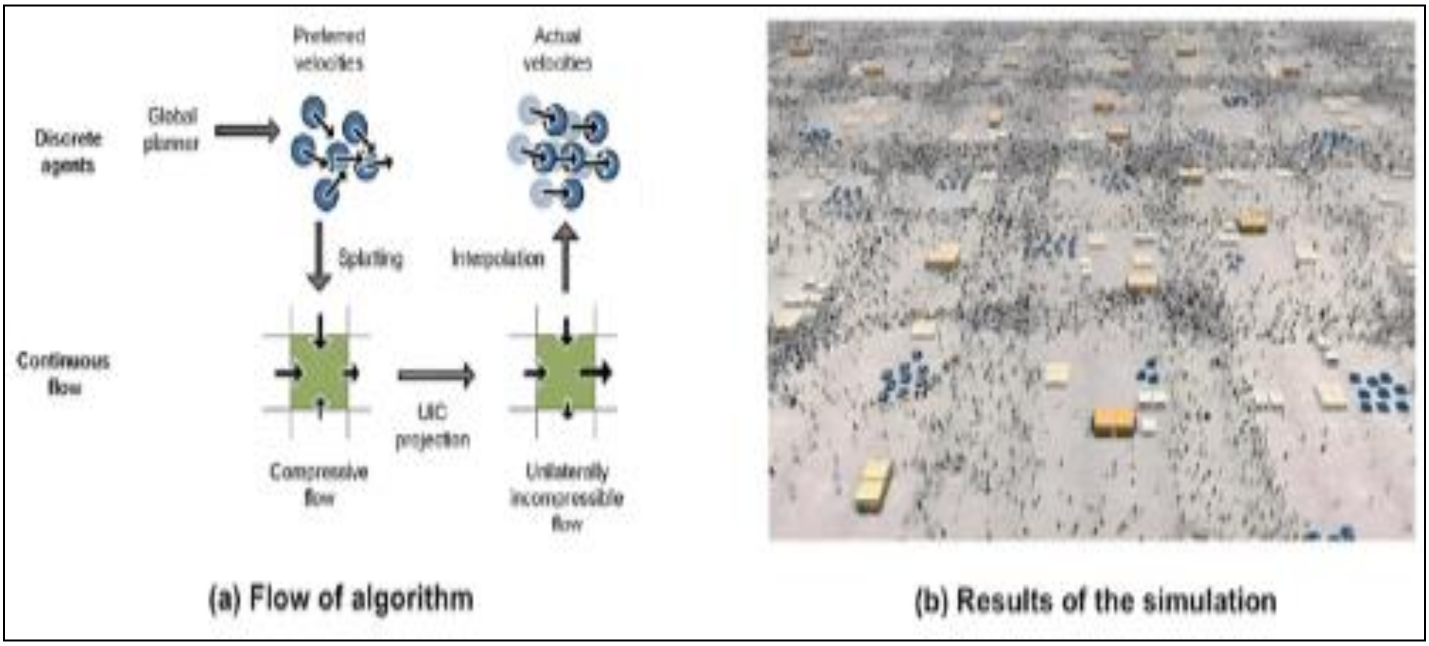

Fig 6 The Complete Sequence of the Aggregate Dynamics [47].

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➢ *Potential Field-Based Modelling*

Potential-based models are widely utilized for simulating large-scale crowds. These models involve partitioning the environment into grids and constructing dynamic fields. One specific approach proposed in [48] is called "Flow Tiles," which focuses on generating divergence-free velocity fields and enhancing flow-like crowd simulations. Nevertheless, it should be acknowledged that the process of assembling a limited number of template flow tiles may not be interactive.

A groundbreaking method called the interactive navigation field approach was devised to guide agents by integrating user-defined guidance fields [49]. These fields, including sketched paths and video footage, can be seamlessly incorporated into the navigation system, as illustrated in Fig 7, ensuring collision-free movement. The interactive nature of this method enables users to edit and customize the navigation field at both global and individual levels. This allows for the simulation of complex behaviors like vortices, lane formations, and group dynamics.To ensure the effectiveness of this method, it is crucial to satisfy Equation (10), which expresses the condition:

$$\|sa - G(X)\| = 1 \qquad (10)$$

By meeting this criterion, the method successfully generates realistic trajectories and individual animations, providing a compelling and immersive crowd simulation experience.

Fig 7 Guidance Field and the Results of Simulation [49].

- *Lagrangian Modelling*

A numerical method called the Lagrangian Discretization solves partial differential equations (PDEs). In this process, PDEs are partitioned into smaller entities or particles and their movements are tracked over time. Specifically, these rules are figured out by the properties of the equation [50]. By discretizing the equation and seeing particle trajectory, an approximate solution can be obtained. For crowd simulation, Lagrangian Discretisation can be used to solve crowd movement equations numerically. The equations are broken down into smaller particles. With rules derived from the equation properties, their trajectory is tracked over time. By using this method, one can generate an approximate solution to simulations involving large crowds of individuals moving together.

- *Game Theory*

Game theory, a branch of mathematics focused on strategic decision-making, plays a crucial role in crowd simulation. A valuable framework for understanding how individuals interact with each other during an evacuation process is provided by this model. In scenarios involving inter-pedestrian conflicts, like obstacle removal or yielder games, game theory can be used to investigate cooperative or defection behavior [51].

Crowd simulations can be used to analyze and predict large groups' behavior under different conditions by using game theory. By using such a macrocosmic approach, we can examine the impact of factors such as the time at which obstacles are removed, how many obstacles are present, and their placement on the overall efficiency and safety of an evacuation. It helps refine crowd management strategies by providing insights into crowd behavior dynamics.

- *Bi-Directional (BM) Macroscopic Modelling*

The Bi-directional Macroscopic (BM) model offers a macroscopic approach to crowd simulation, considering crowds as a collective entity rather than focusing on individual elements. Based on fundamental flow diagrams, the BM model accurately predicts crowd movement and captures experimental data by relating pedestrian fluxes to densities [52]. As a result of this model, improved prediction models and real-time optimization strategies for managing

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large groups of people can be developed. In addition to providing insights into crowd behavior, it enhances crowd management techniques.

C. *Mesoscopic crowd simulation modelling*

Mesoscopic simulation models bridge microscopic and macroscopic approaches, representing pedestrian movement within crowds more realistically. As opposed to microscopic models, which focus on individual pedestrians, and macroscopic models, which analyse aggregate crowd behaviour, mesoscopic models combine both perspectives. Simulating large-scale and dense crowd scenarios in mesoscopic models is done by treating the crowd as one continuous entity. The crowd's movement is determined by potential fields or fluid dynamics. In the case of crowd path planning and collision avoidance, a global problem solver is used, without focusing on individual-level interactions between virtual agents and their environments.

Various mesoscopic models have been developed in crowd motion. These models include dynamic group behaviour, interactive crowd formation, social psychological crowds, and hybrid models that integrate both microscopic and macroscopic behaviours. Through consideration of both individual characteristics and collective behaviours such as density and flow rate, these models aim to capture crowd dynamics complexity.

➢ *Mesoscopic pedestrian flow model types*

- *Dynamic Group Behaviour*

Group dynamics refers to the study of collective behaviours and psychological processes within social groups, as well as interactions between different groups. It aims to identify the general principles underlying group phenomena through dynamic analysis. The term "group dynamics" was coined by Lewin [53], who used it to describe interactions and dynamics between individuals and groups. In this context, a social group can be defined as a cohesive unit composed of two or more individuals who interact and exchange information with one another. It is important to note that a social group is not merely a collection of individuals but also exhibits social cohesion, such as people walking together or forming lines. Group dynamics can be observed in various contexts, such as friends, families, or colleagues walking together. These collective behaviours contribute to the human crowd's distinctive characteristics.

An analysis of and evaluation of small groups' local behaviours was conducted by the authors [54], focused on investigating the relationships within and between groups, considering three distinct walking patterns: line-like, v-like and river-like formations, as given in Fig 8.

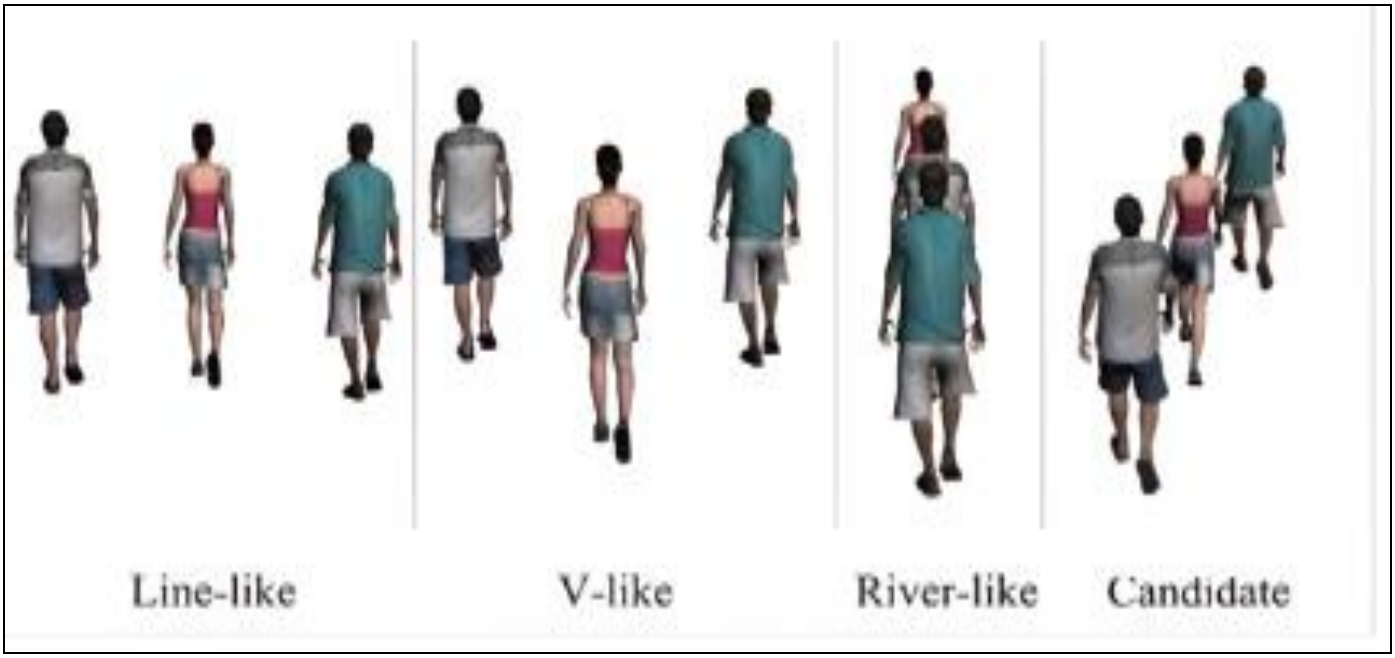

Fig 8 Distinct Walking Patterns in Groups. [54]

In a different investigation [55], a dynamic model for group behaviour was proposed, which utilized the concept of the least effort principle which minimizes energy expenditure for agents navigating through the environment, to promote coordinated group navigation and support both intra-group and inter-group interactions, as shown in Fig 9. It extends the reciprocal collision avoidance approach to enable collision avoidance between both groups and agents, resulting in collision-free and coherent trajectories. The approach's effectiveness is showcased in interactive simulations with hundreds of agents, providing realistic trajectory behaviours aligned with real-world observations.

This model established a clear definition of a group by considering the transitive closure of individuals' positions and velocities, as demonstrated in Equation (11):

$$(a \sim b) \equiv (\|\mathbf{p}a - \mathbf{p}b\| < \epsilon p \wedge \|\mathbf{v}a - \mathbf{v}b\| < \epsilon v) \qquad (11)$$

This Equation (11) ensures that individuals within the same group exhibit similar positions and velocities.

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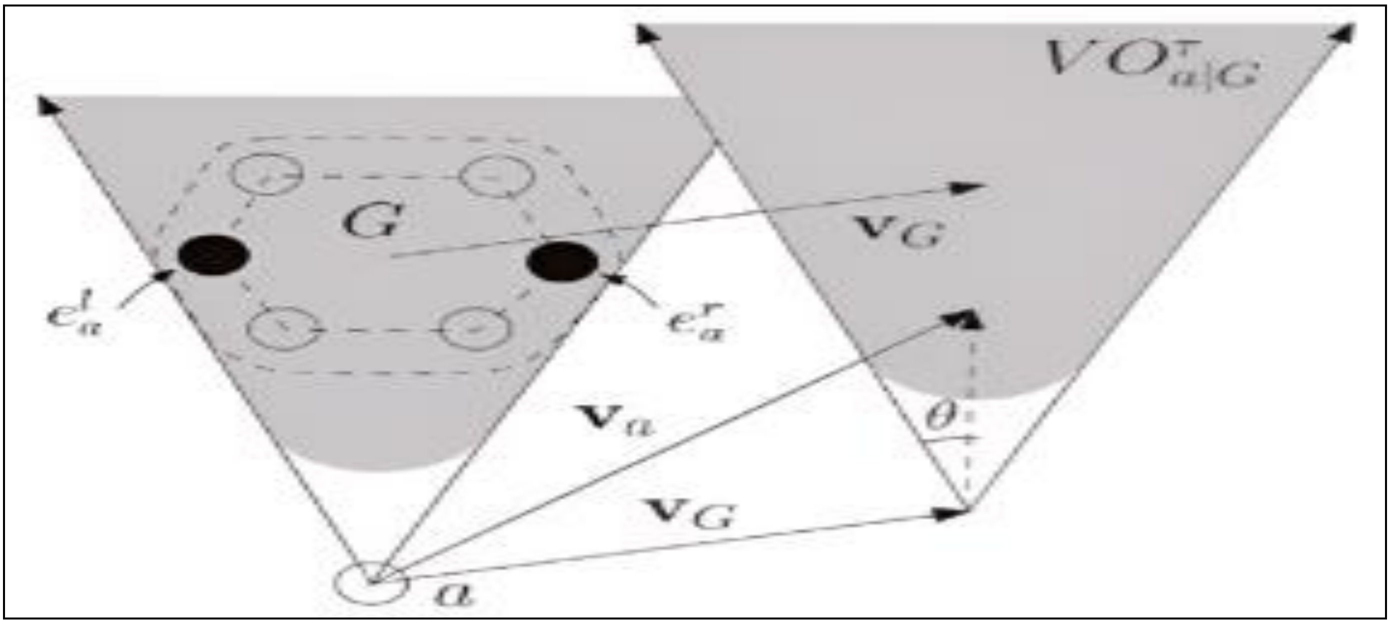

Fig 9 Agent-Group Interactions. [55]

- *Interactive Crowd Formation*

The application of interactive crowd control technology extends to various domains, including visual effects and computer games. These algorithms find utility in real-time strategy (RTS) games like Command & Conquer and StarCraft II, as well as in visual effects for simulating parades, war scenes, and more.

In 2004, the "CrowdBrush" framework was introduced, allowing designers to manipulate crowds in a two-dimensional screen environment, as depicted in the Fig 10[56]. By adding, removing, and modifying crowd members, as well as generating realistic animations, designers can interact with the crowds using a 2D screen and map them to corresponding 3D entities. Building upon this, the "Motion Patches" approach was developed to capture real-world human motion data [57]. Through meticulous analysis of geometric attributes and environmental regularities, motion patches were annotated with precise motion data, forming a directed graph representation, as shown in Fig 11. These patches were seamlessly stitched together to construct environments, enabling interactive control over individual motion. This concept was extended to include both dynamic and static objects, resulting in the concept of "Crowd Patches" [58]. This advancement has opened new possibilities for capturing and simulating crowd behaviours in virtual environments. Walking companions were considered in [59] to enhance the capabilities of "crowd patches".

Fig 10 Interactive Crowd Formation using "Crowd Brush". [56]

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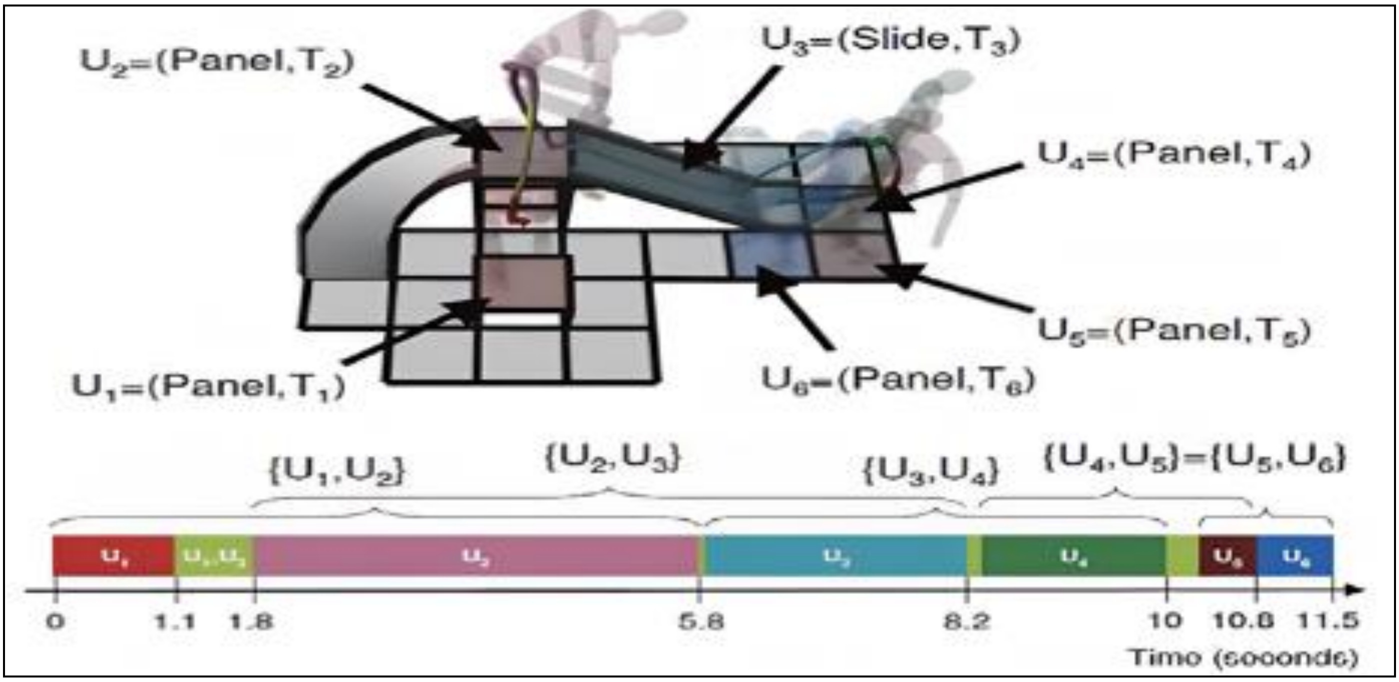

Fig 11 Motion Patches. [57]

In a study by Jordao et al. [60], a technique called "Crowd Sculpting" was proposed, enabling the editing of temporal and spatial crowd motion through intuitive gestures such as stretching, deforming, segmenting, and merging. Another method, "Cage-based Editing" [61] was introduced to facilitate the manipulation of large-scale crowd animation and complex interactions in real-time, providing users with an intuitive editing experience.

- *Social Phycological Crowds*

Human behaviour is greatly influenced by personality traits and theories of emotion contagion, which are captured by different models such as the OCEAN model [62] and the PEN model [63]. These models provide valuable insights into human personality dimensions, including Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism in the OCEAN model, and Psychoticism, Extraversion, and Neuroticism in the PEN model. These frameworks have been utilized in crowd simulation research, particularly in modelling diverse crowd behaviours like Aggressive, Shy, Assertive, Tense, Impulsive, and Active [64], as shown in Fig 12. By establishing mapping relationships between simulation parameters and personality traits, realistic behaviours can be generated without relying on specific equations or formulas. Emotion contagion can be effectively achieved by quantifying the level of each personality component through the utilization of either the OCEAN or PEN models.

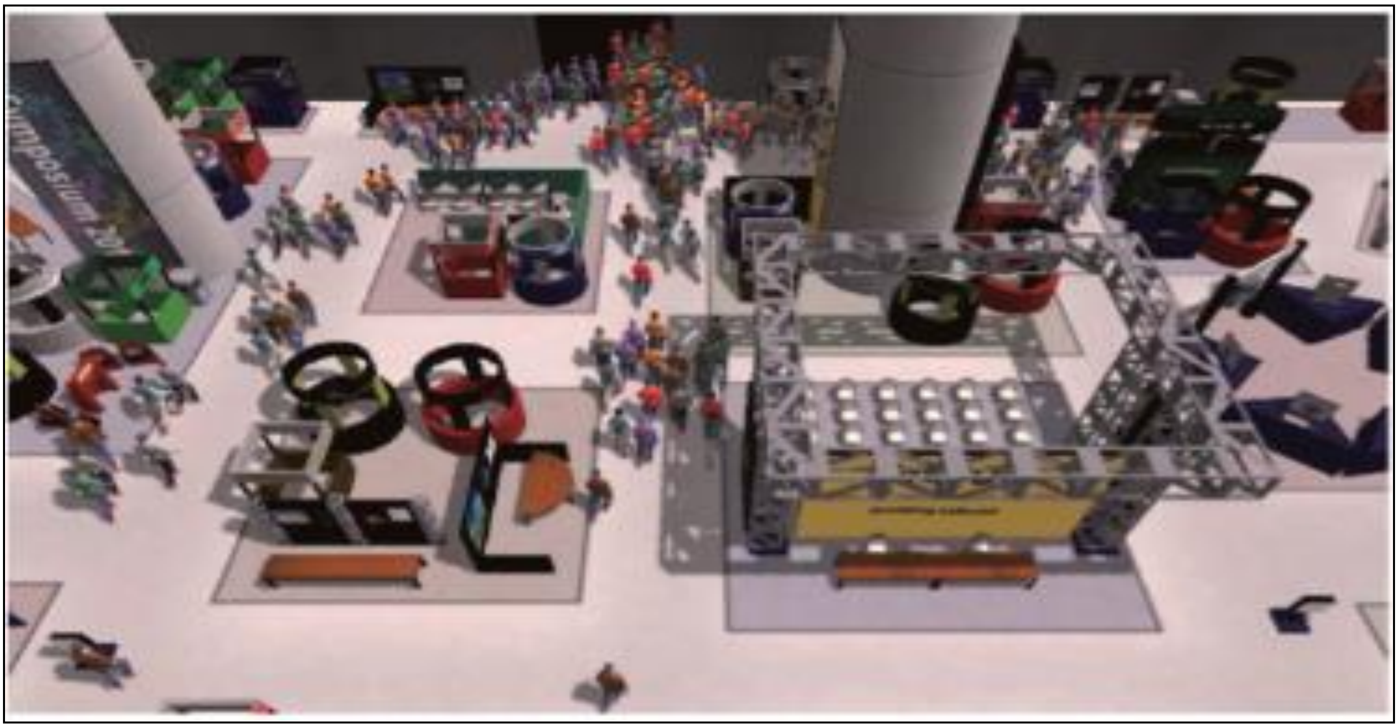
Fig 12 Modelling Heterogeneous Crowd Simulation Based on Personality Traits. [64]

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Crowd simulation extensively employs various emotion contagion models, namely the OCC (Ortony, Clore, Collins), PAD (Pleasure Arousal Dominance), ASCRIBE, and ESCAPES (Emotional States and Coping Abilities for Personalized Evacuation Simulations) models. The OCC model [65] effectively classifies emotions into 22 distinct categories, enabling comprehensive emotion representation across different cultures and individuals. Its widespread adoption in crowd simulation is attributed to its computationally straightforward nature. The PAD model [66] employs three dimensions, namely Pleasure, Activation, and Dominance, to capture the nuances of 42 other emotion scales. ASCRIBE [67] utilizes a multi-agent approach to simulate collective emotions within groups. Conversely, the ESCAPES model [68] incorporates agent types, emotional responses, information exchange, and interactive behaviours to accurately replicate evacuation scenarios, considering factors such as forgetfulness, the prevalence of intense emotions, collective herding behaviour, delays before evacuation, family dynamics, and the influence of authorities.

IV. SIMULATION APPROCHES: EVALUATION AND URBAN APPLICATIONS DISCUSSION

Using SWOT (Strengths, Weaknesses, Opportunities, Threats) analyses, a concise yet comprehensive overview of each model type is provided in this section, highlighting the capabilities, limitations, potential applications, and associated risks associated with each model type. Various fields, including urban planning, emergency management, and public safety, can benefit from this evaluation as a resource for identifying areas of improvement, potential research directions, and practical implementation considerations.

There are distinct benefits and challenges associated with different approaches to crowd modeling. Microscopic models, as demonstrated in Fig 13, are excellent at capturing individual behaviors and interactions, offering high-resolution simulations useful for emergency management and urban planning, but they are limited in scalability. How macroscopic models are effective in simulating crowd movements and optimizing traffic flows is illustrated in Fig 14, even when including broad cultural and infrastructural factors, yet they lack individual-level detail. Mesoscopic models, highlighted in Fig 15, serve as a middle ground, balancing individual behaviors and group dynamics while also taking psychological and social factors into account.

Through these diverse applications, the complementary nature of different modelling approaches becomes evident, and Fig 16 summarizes the taxonomical framework of types of crowd simulation models, highlighting their key differences in terms of general definition, core mechanisms, key elements, structural differences, unique characteristics.

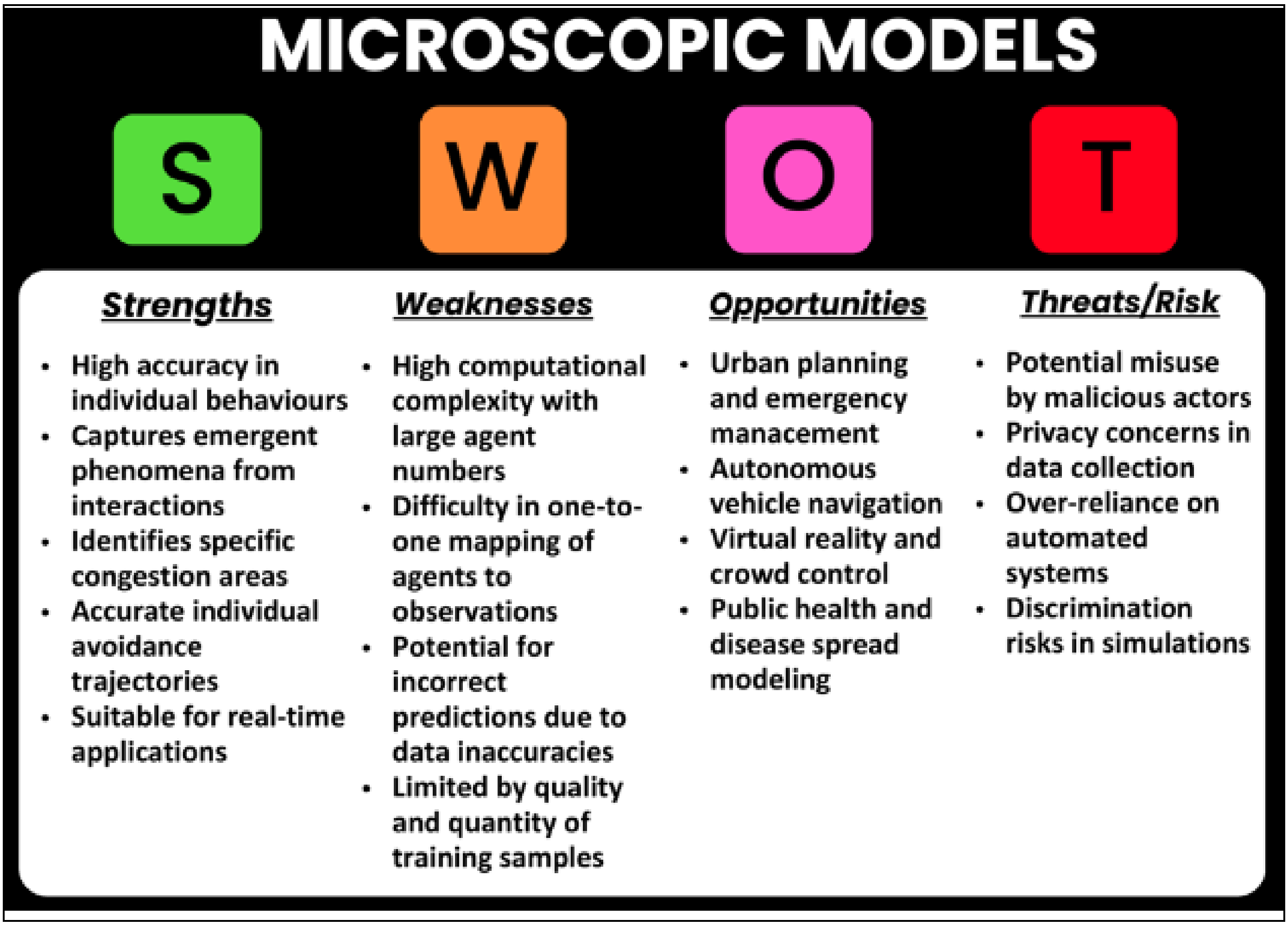

Fig 13 SWOT Framework for Microscopic Crowd Simulation Models.

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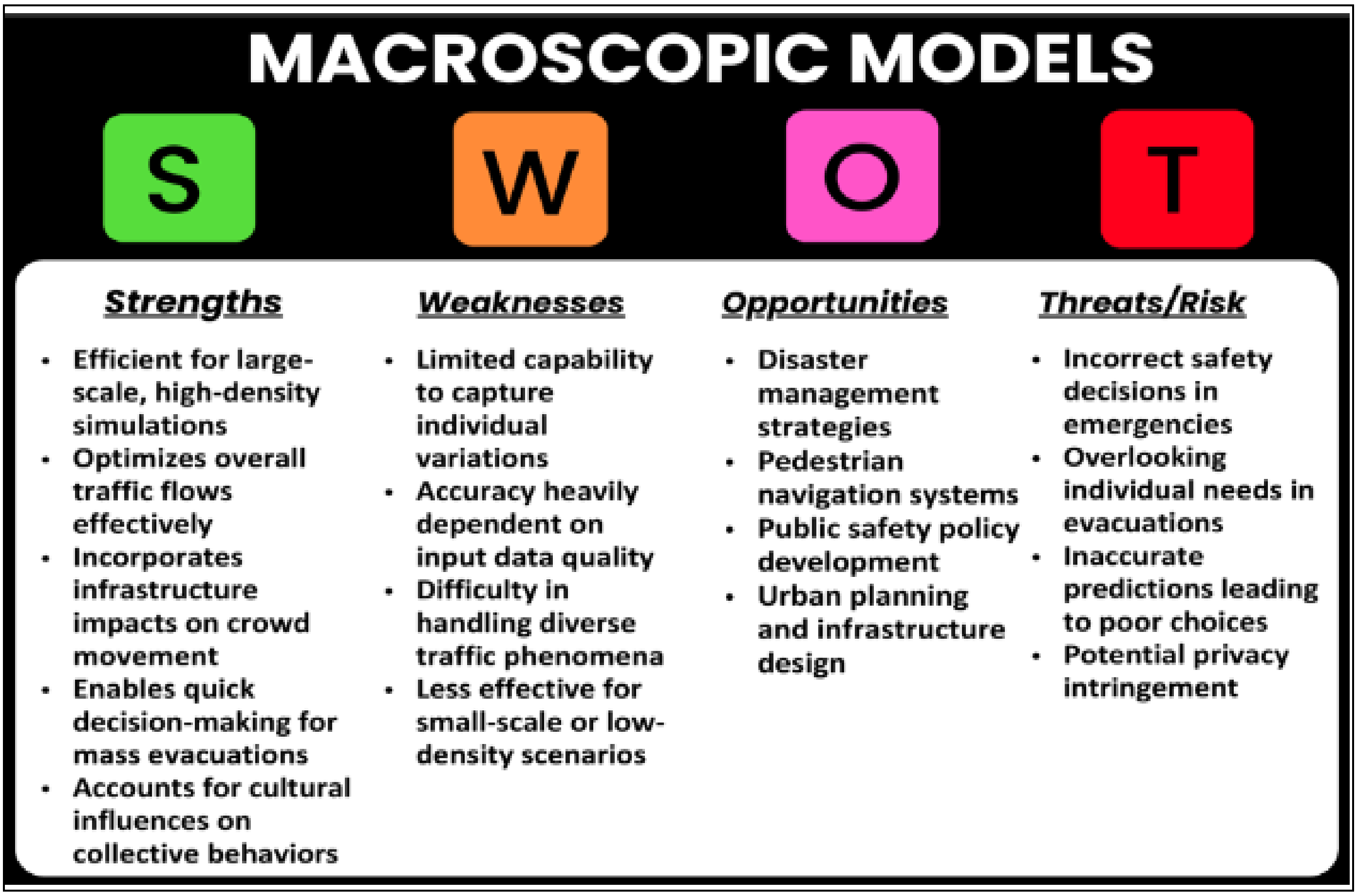

Fig 14 SWOT Framework for Macroscopic Crowd Simulation Models.

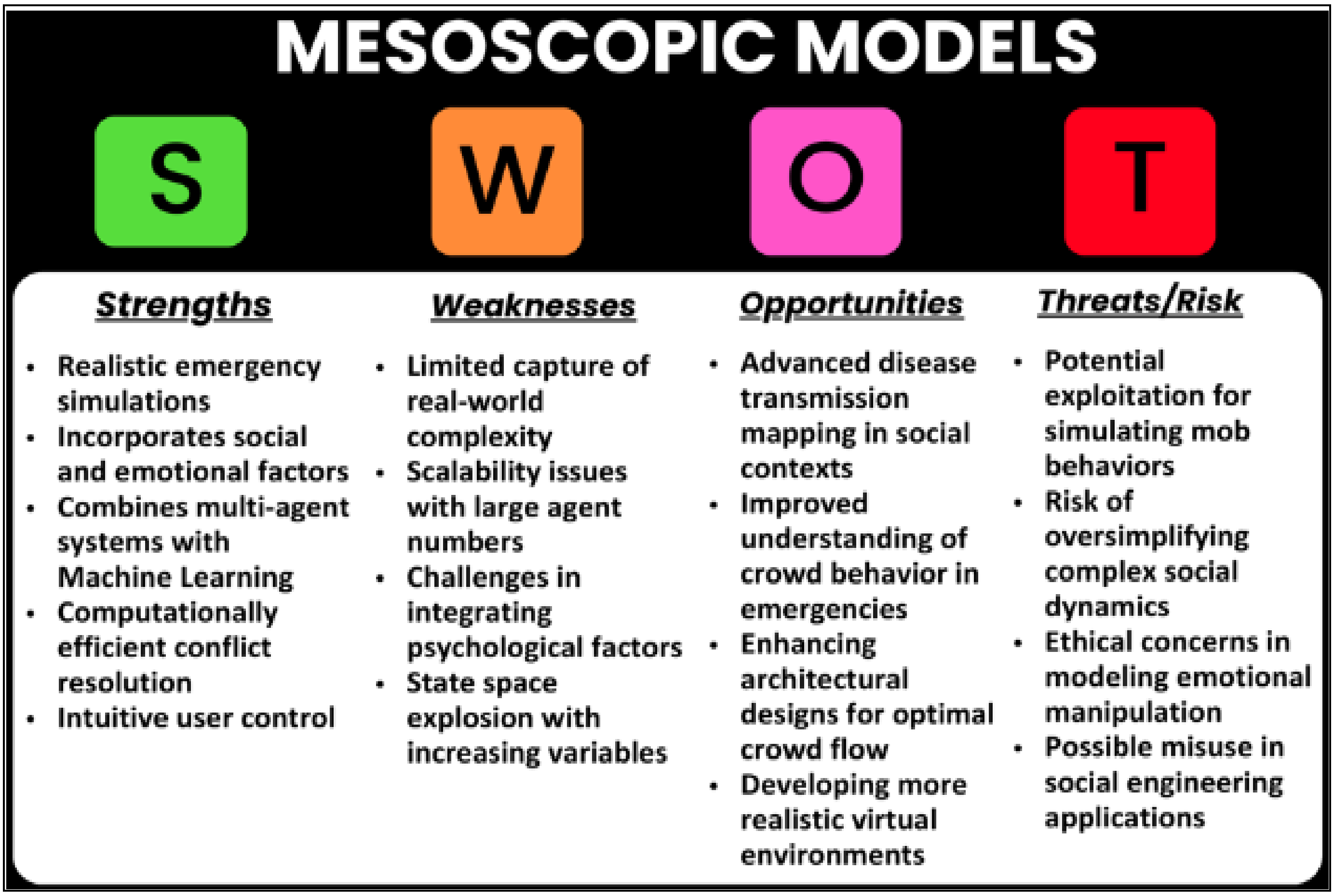

Fig 15 SWOT Framework for Mesoscopic Crowd Simulation Models.

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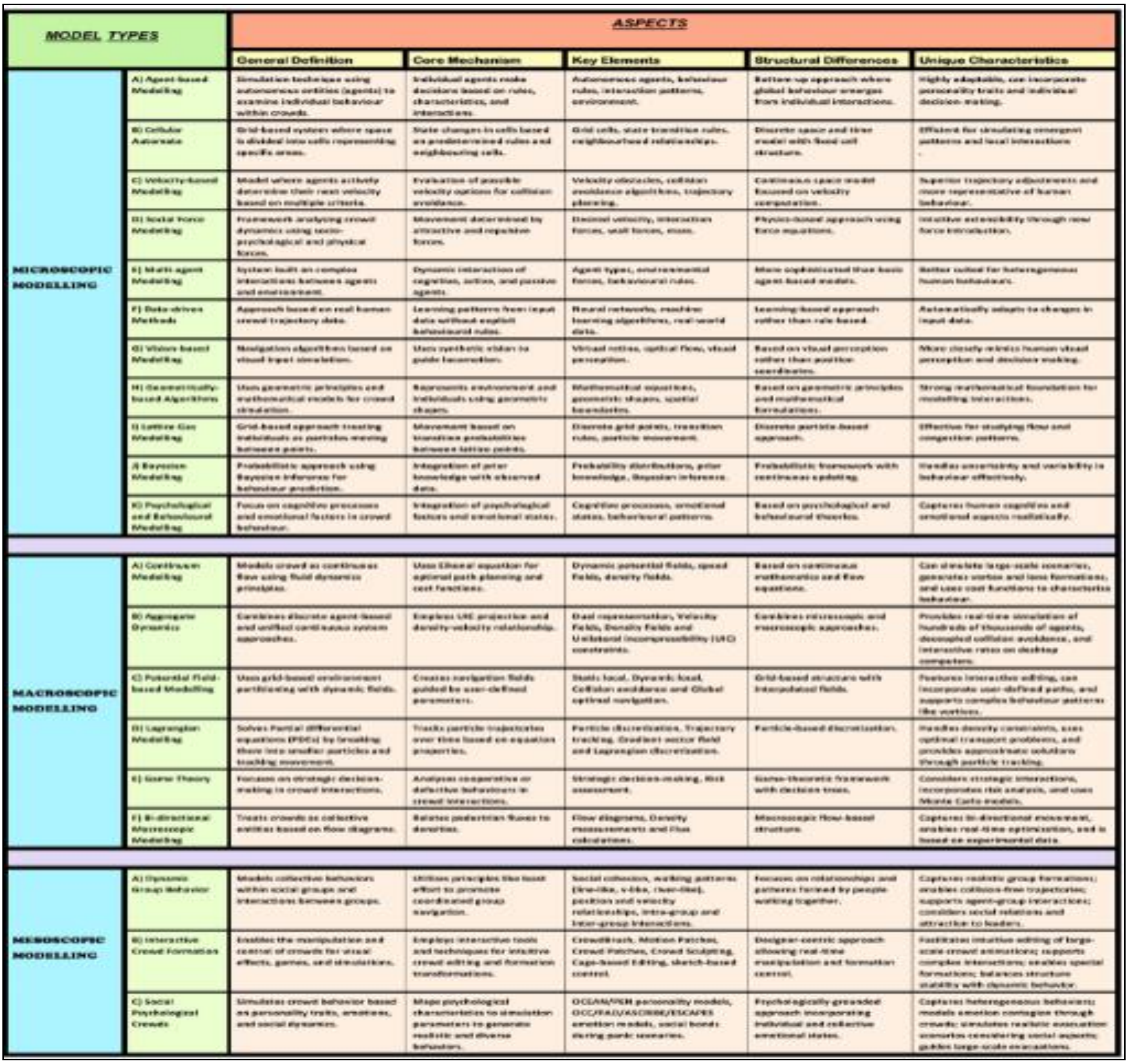

Fig 16 Taxonomical Framework of Crowd Simulation Model's types.

This comparative analysis helps in understanding how each model contributes uniquely to crowd simulation and when each might be most appropriate. There is a distinct advantage to each model type: microscopic for detailed interactions, macroscopic for large-scale patterns, and mesoscopic for flexibility. While each scale of analysis offers unique insights into urban planning challenges, their integration allows for more comprehensive and effective solutions. Planning professionals can select and implement right modelling approaches for specific urban development challenges by understanding these applications. Future research should focus on addressing each model's limitations: improving computational efficiency and data practices for microscopic models, integrating more granular data for macroscopic models, and refining psychological factor integration and validation methods for mesoscopic models, ultimately enhancing their applicability across diverse scenarios.

V. CHALLENGES AND CONCLUSION

Ultimately, this research study has extensively explored the multifaceted domain of crowd simulation, providing valuable insights into its evolution and delving into various modelling approaches and their classifications through a comprehensive analysis. It is consistent with the examined studies that microscopic models accurately capture individual behaviour and micro phenomena, such as leadership, group dynamics, and lane formation. Furthermore, macroscopic models have distinct advantages when it comes to simulating the movement of crowds collectively, especially in densely populated situations. It has been recognized that mesoscopic models provide a bridge between microscopic and macroscopic approaches, effectively incorporating both individual characteristics and collective behaviours.

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No matter what, it is crucial to acknowledge that current crowd simulation methods primarily cater to specific applications. This indicates the need for a flexible and robust framework that accommodates multiple scenarios. Consequently, the development of such a crowd simulation framework capable of supporting a wide array of applications remains a grand challenge in the field. Even amid significant advancements, crowd simulation still faces several challenges that require attention and further research, including the following:

- Incorporating behavioural attributes: Crowd simulation models' ability to accurately capture and incorporate behavioural attributes, such as individual decision-making, social interaction, and emotional contagion, is crucial. During emergency evacuations, this involves modelling and conveying dynamic emergency information to rescue workers, as well as modelling on-site dynamics. When these elements are successfully incorporated into simulations, safer evacuation plans can be designed. Learning frameworks should be integrated with real-world data to enable supervised learning of crowd movement trajectories and unsupervised learning for adaptive models based on essential features.
- Real-world data collection: Obtaining authentic real-world panic crowd data for model learning and validation poses a significant challenge. Using video sequences captured from multiple cameras within a scene, researchers can reconstruct the overall motion state by integrating fragmented data. It allows comprehensive and essential simulation information.
- Usage of cognitive science: It is essential to incorporate psychology and sociology insights into computer algorithms for modelling confrontational crowd behaviour, such as riots and demonstrations. Physiological, emotional, physical, mental, and appearance characteristics must be encompassed in comprehensive models to accurately portray phenomena such as shoving, pushing, and trampling. The absence of reliable real-world crowd behaviour data in extreme cases, however, hinders realistic simulations. To model more autonomous and intelligent crowds, it is necessary to combine artificial intelligence with social psychology and physical laws.
- Balancing efficiency with accuracy: Crowd simulation models need to be enhanced, especially in real-time or cloud-based scenarios, to improve efficiency and performance. With technologies like 5G and remote rendering, there is an opportunity to improve rendering quality, efficiency, and data transfer. Simulation of large-scale realistic crowds requires careful consideration of computational resource requirements. These challenges can be overcome by integrating distributed parallel computing and deep learning techniques.

In addressing these challenges and exploring new directions in these areas, crowd simulation will continue to advance, enabling more realistic and effective simulations across a wide range of applications in the future.

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