A Systematic Analysis of Subgroup Research in Pedestrian and Evacuation Dynamics

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***Abstract*— Pedestrian and evacuation dynamics provide valuable insights into the understanding of human collective motion and have important implications for architectural design, safety management, and transportation science. In social and biological systems, the macroscopic patterns are displayed at the group level, whereas the microscopic behaviors are presented at the individual level. As an intermediate layer, subgroups play a crucial role in linking these two distinct levels of observation and have become one of the important research topics in this field. However, a comprehensive review is still lacking for summarizing current advancements around this topic. Therefore, this paper proposes a survey framework to conduct a systematic review of subgroup research from the following four aspects: data collection and extraction, analysis of phenomena and behaviors, modeling and simulations, and applications and solutions. More critically, a series of research gaps in each aspect are explicitly determined to help researchers grasp unsolved problems. Finally, we present future avenues to narrow the research gaps, which are expected to bring inspiration and guidance for subsequent studies.**

***Index Terms*— Subgroup research, pedestrian and evacuation dynamics, current advancements, research gaps, future avenues.**

I. INTRODUCTION

IN SOCIAL and biological systems, from bacteria [1] to human groups [2], including flocks of insects [3], birds [4], fish [5], and mammals [6], extraordinary patterns of collective motion have always been exhibited. The collective patterns originate from individual interactions, resulting in a slew of research findings on collective behavior from the microscopic scale (individuals) to the macroscopic scale (groups) [7]. Collective motion displays diverse spatio-temporal patterns, which are caused by the stimulating effects of the environment and peers [8], [9]. These stimuli are manifested as changes in speed, acceleration, direction, and steering angle of individuals at the microscopic scale, while at the macroscopic scale, they trigger corresponding transitions in group behaviors and states [10], [11]. To understand the fundamentals of crowd motion and manage evacuation effectively, pedestrian and evacuation dynamics have become a key research field [12]. Subgroups, as an intermediate layer from isolated pedestrians to human crowds, refer to those who are geographically close and attempt to move in a congregated form. Empirical observations indicate that subgroups of 2-4 persons are prevalent in human crowds [13], [14], but subgroups of more than 4 persons are rare and mostly exist in special situations. Social relationships such as kinship, friendship, and collegiality are always the links connecting members in subgroups [15]. Therefore, studying the subgroup and its corresponding mechanisms in pedestrian and evacuation dynamics is an important undertaking.

In the past decades, a large number of classical reviews have appeared on the subject of pedestrian and evacuation dynamics. For data collection and extraction, Haghani and Sarvi [16] discussed a variety of methods for data collection, as well as their advantages and disadvantages. Shi et al. [17] systematically evaluated empirical data collection considering the hierarchy of movement complexity. By analyzing data collection methods for studying pedestrian behavior, Feng et al. [18] explored the possibility of employing new techniques for research. Regarding the analysis of phenomena and behaviors, Helbing et al. [19] reviewed collective motion patterns interpreted as self-organization phenomena in pedestrian dynamics. Duives et al. [20] assessed eight motion base cases and six self-organization phenomena in crowd movement situations. Dong et al. [21] summarized the research progress on pedestrian behavior and characteristic extraction involving self-organization phenomena, fundamental diagrams, and route choice behavior. In terms of modeling and simulations, Zheng et al. [22] identified seven methodological approaches for crowd evacuation in a building, as well as their benefits, drawbacks, and applicability. Bellomo and Dogbe [23] and Vermuyten et al. [24] evaluated the performance of simulation models from the aspect of vehicular traffic, crowd phenomena, and optimization design. Detailed reviews of specific models such as fluid dynamics models [25], social force models [26], and cellular automata models [27] were also presented. For applications and solutions, Helbing et al. [28] discussed the improved design solutions for pedestrian facilities based on self-organized pedestrian crowd dynamics. Caramuta et al. [29] examined the features, potentialities, inputs, and outputs of pedestrian simulation softwares. However, these reviews rarely involve the contents with regard to subgroups, making it imminent to summarize the research on this subject.

Up to now, there have been few reviews related to subgroups in pedestrian and evacuation dynamics. Cheng et al. [30] summed the group size, walking speed, and walking behavior

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in pedestrian group dynamics, and elaborated the modeling approaches of subgroup behaviors as well. Templeton et al. [31] classified small group types into non-perceptual groups, perceptual groups, and cognitive groups by critically reviewing crowd modeling literature, and called for future modeling of group behavior to be more closely integrated with socio-psychological research. Nicolas and Hassan [32] reviewed the definition, prevalence, empirical characteristics, effects on collective dynamics, and numerical models of social groups. Hu and Bode [33] quantitatively integrated studies related to social groups and used meta-analysis to point out that there is insufficient evidence on whether social groups have an effect on the egress times of pedestrian crowds. Nevertheless, all these reviews do not cover a broad range of topics in current advancements of subgroup research, leading to difficulties in deriving critical research gaps and future avenues.

Therefore, we attempt to sort out a comprehensive review of subgroup research in pedestrian and evacuation dynamics, which is essential to provide effective guidance and valuable insights for subsequent studies. The primary contributions of this paper are listed as follows: (1) Formulating a complete survey framework for guiding the literature review of subgroup research. (2) Presenting the most thorough review to date from four aspects: data collection and extraction, analysis of phenomena and behaviors, modeling and simulations, and applications and solutions. (3) Based on current advancements in each aspect, a series of research gaps are explicitly determined. (4) Highlighting future avenues of subgroup research and contributing open perspectives for researchers in related fields. It should be noted that various publications probably use different descriptions, such as "social groups", "small groups", and "pedestrian groups", etc., which are all included in the category of "subgroups" in this paper.

The rest of this paper is organized as follows. The review methodology including literature selection and survey framework is presented in Section II. In Section III, the methods of data collection and extraction are reviewed. Section IV summarizes the studies related to the analysis of phenomena and behaviors. Section V recalls different modeling and simulation approaches. In Section VI, the research progresses on applications and solutions are outlined. Finally, the conclusions and future avenues are pointed out in Section VII.

II. Review Methodology

This section describes the review methodology, which mainly includes two aspects: First, the literature search and inclusion criteria help to achieve the selection of publications. Second, the survey framework of subgroup research is proposed to guide the subsequent literature review.

A. Literature Search and Inclusion Criteria

The literature search was implemented on three electronic databases including "Web of Science", "Scopus", and "Google Scholar" in October 2021. We concentrated on peer-reviewed publications from the past two decades (from 2000 to 2021) during which significant advances in pedestrian and evacuation dynamics have been made, whereas only a small number of seminal works from before 2000 were considered. Note that publications were limited to English language and were generally included in journals, conferences and book chapters, rather than news, reports and interview collections. We applied a series of key terms and their combinations to "title", "abstract" and "keywords" in the search options of these databases, involving but not restricted to "pedestrian", "crowd", "evacuation", "subgroup", "social group", "small group", "pedestrian group", "data", "observation", "experiment", "phenomenon", "behavior", "analysis" "model", "simulation", "validation", "application", and "solution". The collection of searched literature was further perfected using the method of forward (i.e., finding citations to a paper) and backward (i.e., finding citations in a paper) snowballing [34].

To ensure the reliability of the literature review, the corresponding inclusion criteria for selecting eligible publications are listed below: (1) Research publications on subgroups are taken into account, whereas survey or review publications related to subgroups are excluded. (2) Studies of data aspects need to ensure that the extracted data are relevant to subgroups or used for subgroup research. (3) Studies of analytical aspects require conducting scientific explorations on the attributes, characteristics, phenomena, and behaviors of subgroups. (4) Studies of modeling aspects necessitate reproducing the behavioral characteristics of subgroups such as walking patterns, avoidance strategies, and emergency escapes. (5) Studies of applied aspects should highlight the noticeable impacts of subgroup findings on relevant application areas. In this case, we further checked the publications that belong to the scope of the literature search, 121 of which tallying with these inclusion criteria were ultimately retained for the detailed literature review in subsequent sections.

B. Survey Framework of Subgroup Research

Given the extensive publications on subgroup research in pedestrian and evacuation dynamics, it is vital to formulate a complete survey framework for guiding the literature review. Therefore, the survey framework is presented in Fig. 1, which covers data collection and extraction, analysis of phenomena and behaviors, modeling and simulations, and applications and solutions. These four aspects are interrelated to form a closed-loop structure, and the specific correlations between them are listed as follows: (1) The collected and extracted data are frequently treated as driving factors for motivating the analysis of phenomena and behaviors, and can also be utilized to calibrate model parameters and evaluate the performance of models. (2) The potential laws of phenomena and behaviors may be used to support the construction and optimization of models, in turn, these models can reproduce subgroup behaviors and empirical phenomena. (3) The modeling of subgroups can forwardly provide guidance for realistic applications and solutions, whereas they may reversely support model refinements by validating the effectiveness and performance of models. (4) The analytical findings of subgroups play a regulatory role in multiple aspects of applications and solutions, which on

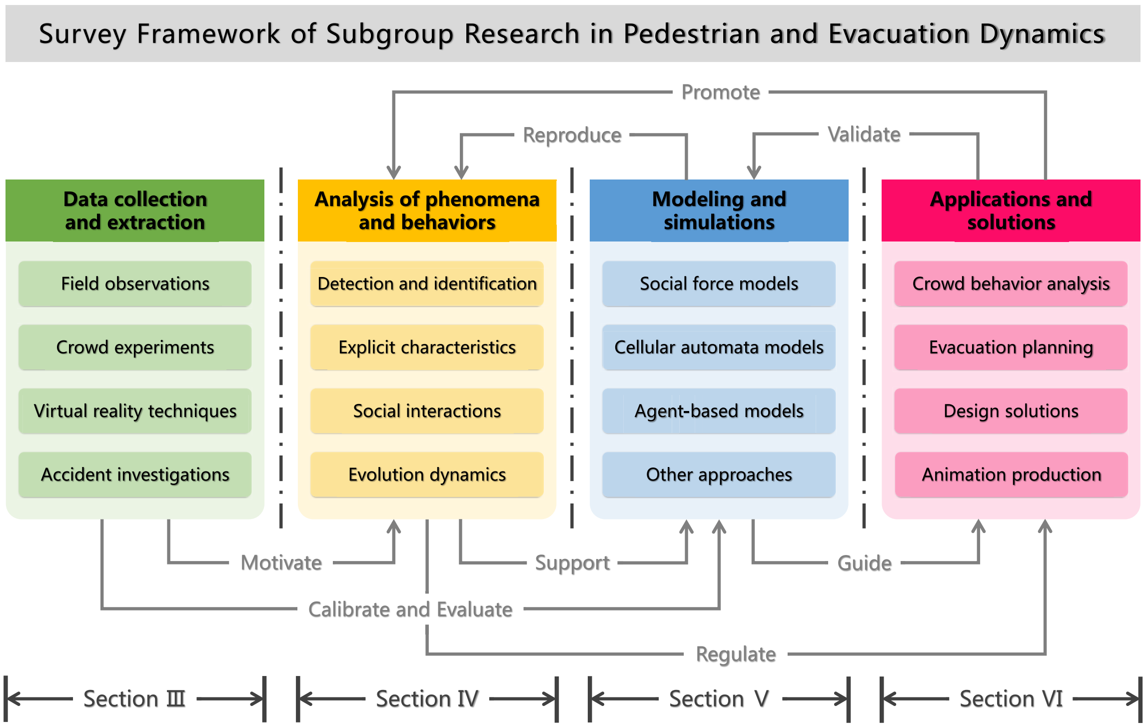
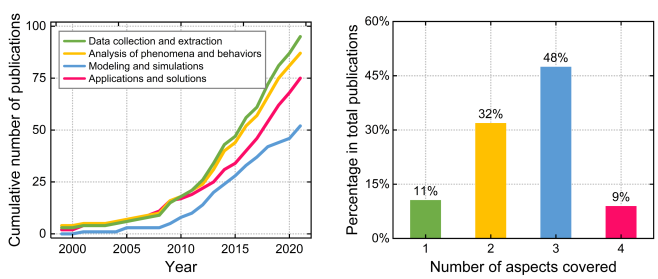


Fig. 1. Survey framework of subgroup research in pedestrian and evacuation dynamics. The rectangular areas with various colors represent different aspects, with grey arrows reflecting the correlations between these aspects.



(a) (b)

Fig. 2. Statistical analysis of the publications selected in this paper. (a) Cumulative number of publications for each aspect as a function of year. (b) Percentage of the number of aspects covered in total publications.

the contrary can facilitate further analysis, comparison, and validation of phenomena and behaviors.

It is worth analyzing the comprehensiveness and representativeness of the proposed survey framework. These four aspects include a wide range of topics in pedestrian and evacuation dynamics, and most of the classic reviews in this field are based on one or several certain aspects [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29]. To demonstrate the research on subgroups also universally involves these aspects, the specific aspects and correlations corresponding to the publications selected in this paper are summarized in Table I. It is obvious that each publication covers, more or less, parts of specific aspects and correlations, which preliminarily confirms the comprehensiveness of this survey framework. In addition, Fig. 2 displays a statistical analysis of the publications selected in this paper. It can be noted from Fig. 2(a) that the cumulative number of publications for each aspect increases simultaneously after 2010, revealing the rapid development of subgroup research corresponding to these four aspects in the survey framework. Fig. 2(b) illustrates that a publication generally contains multiple aspects (i.e., accounting for 89%), with two and three aspects dominating. These results further indicate that this survey framework is highly representative of subgroup research, which is beneficial for clarifying specific aspects and ascertaining potential correlations. It should be noted that similar survey frameworks can also be established for other subjects (e.g., cooperation, navigation, and decision-making) in pedestrian and evacuation dynamics.

III. Data Collection and Extraction

In this section, four common data collection and extraction methods are reviewed, including field observations, crowd experiments, virtual reality techniques, and accident investigations, which are evaluated from the view of applicable scope, controllability, data features, and expense cost. Last, we determine three research gaps in this aspect: (1) Capturing comprehensive subgroup data in complex or emergency scenarios. (2) The representativeness of subgroup data acquired from crowd experiments is limited. (3) The current lack of collection methods for obtaining multifaceted subgroup data.

A. Field Observations

Field observations generally utilize equipment (e.g., cameras, sensors, and mobile devices) to record the regular movements of pedestrians in public places such as streets, malls, stations, and plazas, for the purpose of acquiring pedestrian data under natural conditions.

TABLE I
SPECIFIC ASPECTS AND CORRELATIONS CORRESPONDING TO THE SELECTED PUBLICATIONS

Year	**Author(s)**	**Ref.**	**Specific Aspects**				**Specific Correlations**							
			I	II	III	IV	I→II	I→III	II→III	II→IV	III→IV	III→II	IV→II	IV→III
1953	James	[13]	✓	✓			✓							
1961	Coleman and James	[97]		✓										
1982	McPhail and Wohlstein	[89]	✓	✓		✓	✓			✓				
1983	Sime	[73]	✓	✓		✓	✓			✓				
2001	Tarawneh	[107]	✓	✓		✓	✓			✓				
2001	Musse and Thalmann	[189]			✓	✓					✓			✓
2004	Willis et al.	[182]	✓	✓		✓	✓			✓				
2005	Helbing et al.	[28]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2005	Yang et al.	[139]			✓	✓					✓			
2006	Galea et al.	[75]	✓	✓		✓	✓			✓				
2007	Eisenman et al.	[76]	✓	✓		✓	✓			✓				
2008	Kwon et al.	[188]				✓								
2009	Schultz et al.	[114]	✓	✓		✓	✓			✓				
2009	Singh et al.	[35]	✓	✓	✓		✓	✓	✓			✓		
2009	Drury et al.	[68]	✓	✓		✓	✓			✓				
2009	Drury et al.	[79]	✓	✓		✓	✓			✓				
2009	Nilsson and Johansson	[74]	✓	✓		✓	✓			✓				
2009	Shields et al.	[77]	✓	✓		✓	✓			✓				
2009	Peters and Ennis	[192]	✓	✓	✓	✓	✓	✓	✓		✓	✓		✓
2010	Moussaïd et al.	[36]	✓	✓	✓		✓	✓	✓			✓		
2010	Xu and Duh	[129]	✓		✓			✓						
2010	Qiu and Hu	[149]			✓									
2010	Strawderman et al.	[183]	✓	✓		✓	✓			✓				
2011	Köster et al.	[143]	✓	✓	✓		✓	✓				✓		
2011	Bandini et al.	[140]			✓									
2011	Cui et al.	[177]	✓	✓		✓				✓			✓	
2011	Rastogi et al.	[184]	✓	✓		✓	✓			✓				
2012	Manenti et al.	[151]	✓		✓			✓						
2012	Ge et al.	[39]	✓	✓	✓		✓	✓	✓			✓		
2012	Kjærgaard et al.	[44]	✓	✓		✓	✓			✓				
2012	Federici et al.	[98]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
2012	Karamouzas and Overmars	[156]	✓		✓	✓		✓			✓			✓
2013	Schultz et al.	[99]	✓	✓			✓							
2013	Reuter et al.	[115]	✓	✓	✓		✓		✓			✓		
2013	Seitz et al.	[144]			✓									
2013	Rojas and Yang	[69]	✓		✓			✓						
2013	Yücel et al.	[90]	✓	✓										
2013	Zanlungo and Kanda	[113]	✓	✓			✓							
2013	Vizzari et al.	[141]			✓									
2013	Crociani et al.	[154]	✓	✓	✓		✓	✓	✓					
2013	Ma and Song	[176]	✓	✓		✓	✓			✓			✓	
2013	Park et al.	[190]			✓	✓					✓			
2013	Hediyeh et al.	[108]	✓	✓		✓	✓			✓				
2014	Shao et al.	[40]	✓	✓		✓	✓			✓			✓	
2014	Glas et al.	[42]	✓	✓			✓							
2014	Sen et al.	[95]	✓	✓		✓	✓			✓			✓	
2014	Zanlungo et al.	[104]	✓	✓	✓		✓	✓	✓			✓		
2014	Gorrini et al.	[105]	✓	✓		✓	✓			✓				
2014	Xi et al.	[101]	✓	✓			✓							
2014	Müller et al.	[145]			✓									
2014	Rahman et al.	[159]	✓	✓	✓	✓	✓	✓	✓		✓	✓		✓
2014	Li et al.	[178]	✓	✓		✓				✓			✓	
2014	D'Orazio et al.	[181]	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
2015	Yi et al.	[41]	✓	✓		✓	✓			✓			✓	
2015	Zanlungo et al.	[43]	✓	✓			✓							
2015	Bode et al.	[56]	✓	✓		✓	✓			✓				
2015	Bruneau et al.	[65]	✓	✓		✓	✓			✓				
2015	Huang et al.	[161]			✓									
2015	Huang et al.	[162]			✓									
2015	Wang et al.	[163]			✓									
2015	Lemercier and Auberlet	[152]			✓									
2016	Qin and Shelton	[93]	✓	✓										
2016	Solera et al.	[91]	✓	✓			✓							
2016	Zhao et al.	[37]	✓	✓			✓							

TABLE I

(Continued.) SPECIFIC ASPECTS AND CORRELATIONS CORRESPONDING TO THE SELECTED PUBLICATIONS

2016	Sivers et al.	[78]	✓	✓	✓	✓	✓		✓		✓	✓		✓
2016	You et al.	[100]	✓	✓	✓		✓		✓			✓		
2016	Gorrini et al.	[106]	✓	✓		✓	✓			✓				
2016	Bode	[111]	✓	✓			✓							
2016	Do et al.	[38]	✓	✓		✓	✓			✓				
2016	Wang et al.	[130]			✓	✓					✓			
2016	Elzie et al.	[155]			✓	✓					✓			
2016	Hussein and Sayed	[153]	✓		✓	✓		✓			✓			
2017	Ma et al.	[60]	✓	✓		✓	✓			✓				
2017	Krüchten and Schadschneider	[57]	✓	✓		✓	✓			✓				
2017	Zanlungo et al.	[102]	✓	✓			✓							
2017	Li et al.	[132]			✓	✓					✓			
2017	Lu et al.	[146]	✓	✓	✓	✓	✓	✓			✓	✓		
2017	Zhou et al.	[157]			✓									
2017	Zhao et al.	[150]			✓	✓					✓			
2017	Cepolina et al.	[185]	✓	✓		✓	✓			✓				
2018	Zaki and Sayed	[92]	✓	✓		✓	✓			✓				
2018	Du et al.	[45]	✓	✓			✓							
2018	Templeton et al.	[52]	✓	✓			✓							
2018	Zhang et al.	[46]	✓	✓	✓	✓	✓		✓		✓	✓		
2018	Kinateder et al.	[66]	✓	✓		✓	✓			✓				
2018	Huang et al.	[70]	✓		✓			✓						
2018	Bera et al.	[71]	✓	✓			✓							
2018	Zhang et al.	[116]			✓	✓					✓			✓
2018	Crociani et al.	[142]	✓		✓			✓						
2018	Zhang et al.	[180]	✓	✓		✓	✓			✓				
2018	Ağıl and Güdükbay	[191]	✓	✓		✓				✓			✓	
2018	Fu et al.	[62]	✓	✓		✓	✓			✓				
2018	Liu et al.	[131]			✓	✓					✓			
2019	Bisagno et al.	[173]	✓	✓		✓				✓			✓	
2019	Crociani et al.	[50]	✓	✓			✓							
2019	Haghani et al.	[58]	✓	✓		✓	✓			✓				
2019	Zhou et al.	[67]	✓	✓		✓	✓			✓			✓	
2019	Zanlungo et al.	[103]	✓	✓			✓							
2019	Fu et al.	[109]	✓	✓		✓	✓			✓				
2019	Yucel et al.	[110]	✓	✓			✓							
2019	Wang et al.	[166]			✓	✓					✓			
2019	Zhang et al.	[174]	✓	✓		✓				✓			✓	
2019	O'Connor et al.	[194]	✓	✓		✓	✓			✓			✓	
2019	Rivalcoba et al.	[193]			✓	✓					✓			✓
2020	Zou et al.	[55]	✓	✓			✓							
2020	Hu et al.	[53]	✓	✓		✓	✓			✓				
2020	Xie et al.	[59]	✓	✓		✓	✓			✓				
2020	Li et al.	[61]	✓	✓		✓	✓			✓				
2020	Prédhumeau et al.	[128]			✓									
2020	Li et al.	[147]			✓	✓					✓			
2020	Sun et al.	[175]	✓	✓		✓				✓			✓	
2020	Fu et al.	[186]	✓	✓		✓	✓			✓				
2021	Ye et al.	[54]	✓	✓			✓							
2021	Li et al.	[94]	✓	✓			✓							
2021	Hu et al.	[51]	✓	✓		✓	✓			✓				
2021	Xie et al.	[133]	✓		✓	✓		✓			✓			
2021	Turgut et al.	[134]	✓		✓	✓		✓			✓			
2021	Li et al.	[135]	✓	✓	✓	✓	✓	✓	✓		✓			
2021	Pan et al.	[158]	✓	✓	✓	✓	✓	✓	✓		✓			
2021	Zhou et al.	[167]			✓	✓					✓			✓
2021	Li et al.	[138]	✓	✓	✓	✓	✓	✓	✓		✓	✓		

Notes: These publications in the table are presented in ascending order by year.
I – Data collection and extraction, II – Analysis of phenomena and behaviors, III – Modeling and simulations, IV – Applications and solutions, and → – Correlation arrow.

The most typical method is to collect videos using cameras and then extract pedestrian data from them. To investigate subgroup phenomena or calibrate simulation models, public sites such as university campuses [35], commercial streets [36], subway corridors [37], and train stations [38] were frequently suitable venues for obtaining relevant data. Cameras were installed in specified locations to collect videos, from which one could manually or automatically extract pedestrian data using softwares (e.g., PeTrack, SIMI Motion). To explore the behavioral characteristics of subgroups, relevant algorithms were quantitatively validated by collecting video sequences from different scenes and inviting coders to manually mark subgroup labels [39]. Even researchers collected crowd videos from hundreds of sites [40] or extracted thousands of trajectories in specific scenes [41] to build pedestrian datasets, which were employed to study subgroups in crowds.

Advanced sensors and mobile devices are also adopted to record spatio-temporal data of pedestrians at different scales. Laser range finder (LRF) [42] and three-dimensional (3D) range sensors [43] enabled high-precision pedestrian tracking to identify subgroups and study the dependence on crowd density of the spatial size, configuration, and velocity. Given that mobile phones are indispensable for pedestrians, digital sensors in mobile phones could be used to collect a series of data such as acceleration, magnetic field, Wi-Fi signals, and audio waves, which were essential for subgroup detection, mobility level classification, and group structure recognition [44], [45]. Furthermore, unmanned aerial vehicles (UAVs) equipped with cameras were able to record videos in those places inaccessible to mobile cameras [46], and filming from a perspective approaching overhead is conducive to resolving problems such as mutual occlusions among pedestrians.

The data obtained from field observations are mainly used for subgroup research in non-emergency situations since it is hard to collect data related to emergency incidents. This method is uncontrollable because there is no control over the conditions such as climates, locations, and behaviors of the observed subjects. Although field observations can ensure the representativeness of data in natural situations, the accuracy is still questionable (e.g., pedestrian occlusions due to angle restrictions [47], calibration errors of lens distortion [48]), and it is also difficult to obtain comprehensive data in emergency situations. Besides, this method necessitates consideration of tasks such as permit approval and equipment installation, and the process of data extraction by manual or semi-automated methods is cumbersome, thereby the cost is relatively high.

B. Crowd Experiments

Crowd experiments refer to the crowd moving according to instructions or set conditions in pre-designed scenarios, from which basic pedestrian data such as trajectory, speed, direction, density, and flow can be obtained. The studies on subgroups are generally carried out by controlled laboratory experiments and evacuation drills.

The data collected by controlled laboratory experiments are utilized to explore the impact of subgroups on traffic dynamics, involving typical scenarios such as corridors, circular (ring) areas, and narrow bottlenecks. The corridor is regarded as one of the most classical scenarios for studying self-organization phenomena and fundamental diagrams [49]. By recording videos in corridor experiments and extracting the trajectories of participants, it was feasible to study the effects of subgroups on unidirectional and bidirectional pedestrian flows [50], [51], as well as to investigate the behavioral differences between physical and psychological crowds [52]. Given that circular (ring) areas allow for reciprocating pedestrian movements, researchers also preferred to adopt such scenarios to examine the behaviors and strategies of subgroups in multi-directional flows [53] and the traffic dynamics of pedestrian flows influenced by dyad subgroups [54]. Controlled laboratory experiments were also conducted in narrowing bottlenecks and obstacle scenarios, aiming to analyze the evolution behaviors of subgroups and the strategies of keeping configuration [55].

Evacuation drills capture data by generating environments with time pressure, involving typical scenarios such as simple rooms and complex buildings. On the one hand, researchers performed evacuation drills in simple makeshift rooms and used cameras to capture the video of experiments. The extracted pedestrian data were utilized to explore how the presence of subgroups interferes with evacuation times [56], [57], how the decision dynamics of subgroups affect evacuation behaviors [58], and how individuals and subgroups behave under different visibility conditions [59]. On the other hand, evacuation drills in high buildings often recorded the behavioral data of participants through cameras deployed at specific locations to investigate the effects of subgroups and social relationships on evacuations [60], [61]. Another study conducted experiments in two connected buildings to explore the impact of emergency signage on the behaviors of individuals and subgroups, with relevant data recorded by DV cameras and head-mounted mini cameras [62].

The data acquired from crowd experiments can be employed in both non-emergency and emergency situations, which depends on the context of research questions on subgroups. This method has high controllability considering it can easily be achieved by controlling the movement of pedestrians through specific scenarios, environmental conditions, time pressure, and rule commands. Crowd experiments are able to ensure more accurate data by selecting the appropriate collection locations. However, the unnatural behaviors of participants are often questioned and the experimental scenarios are relatively simple, which leads to a need to improve the representativeness and comprehensiveness of data. The cost of this method may be pricey since it requires booking sites, building platforms, installing equipment, and inviting participants, in addition to the potential limitations of organizing crowd experiments in the case of COVID-19.

C. Virtual Reality Techniques

Virtual reality techniques, unlike crowd experiments with real humans, are regarded as an emerging and non-negligible data acquisition method for studying pedestrian behaviors [63], [64]. The avatars in virtual environments can be directly operated and observed by participants, which provides more immersive experiences and safer experimental conditions.

The avatar data generated by inviting participants to conduct operation-type experiments are employed to explore the laws of subgroup behaviors and interactions. Based on the trajectory data supplied by operating virtual avatars during obstacle avoidance, it was possible to understand the avoidance behaviors of pedestrians who decide to go through or around subgroups [65]. The impact of exit familiarity and neighbor behaviors on evacuation processes was analyzed by collecting data on participants manipulating virtual avatars [66]. In addition, some researchers allowed players to operate avatars in virtual space and collected data corresponding to three factors: interpersonal distances, interpersonal angles, and avatar postures, which provided a basic computational unit for estimating the probability of social interactions [67].

The assessment data obtained by encouraging participants to undertake observation-type experiments are often used to validate the phenomena, laws, and models of subgroups. In a virtual reality experiment of a mass emergency evacuation, the self-report questionnaire data of participants were utilized to explore the cooperative behavior of subgroup members with social identification [68]. To check the adequacy of models for simulating subgroup behaviors, relevant studies invited participants to interact with virtual subgroups in immersive environments to capture the assessment data concerning subgroup characteristics [69], [70]. According to the overall perception of subgroups in virtual environments, these data were also used to validate the socio-emotional predictive ability of the proposed algorithm [71].

The data extracted by virtual reality techniques are also applicable to subgroup research in both non-emergency and emergency situations. This method is particularly suitable for creating a sense of realism in emergency incidents, and various influences in virtual environments can also be assigned by the program, making it highly controllable. Despite that whether the behaviors of participants facing the virtual environments are representative of those in the real world is debatable, the accuracy of the data generated by the virtual avatars can be guaranteed as they are embedded in the overall systems. The cost of virtual reality techniques is not high since the platform can be set up for repeated experiments and subgroup data can be directly exported and recorded from the system [72].

D. Accident Investigations

Apart from the above methods, accident investigations can be used to obtain relevant data for subgroups as well. This kind of method obtains supporting information closer to real evacuation situations by analyzing disaster and accident reports or interviewing those who have experienced incidents.

Disaster and accident reports provide realistic depictions of the evacuation process in emergency situations, and the data documented in these reports may be different from those in conventional situations. For example, both descriptive records of fire accidents in a seaside leisure complex (in 1973, Great Britain) [73] and video recordings of unannounced evacuations in a cinema theatre (in 1999, Sweden) [74] have been used to investigate the affiliative behavior among subgroup members during emergency incidents. Besides, data records from the Aircraft Accident Statistics and Knowledge (AASK) database were analyzed to emphasize the importance of subgroup social relations for studying evacuation behaviors [75].

Interviewing those who have experienced emergencies is capable of yielding psychological and behavioral data, which can be adopted to guide research on subgroups under panic conditions. Based on the qualitative interview materials from survivors of Hurricane Katrina [76], 9/11 terrorist attacks [77], London underground bombings [78], and multiple emergencies [79], researchers suggested that evacuation studies should not only pay attention to subgroups and the organizations they interact with, but also concentrate on the viewpoints of forming subgroups with assistors or others and the role of shared identity on cooperative behaviors. These empirical data are useful in helping to develop applications of social identity and group psychology in pedestrian simulations.

Accident investigations typically collect data in emergency situations due to the fact that crowds usually feel pressure and urgency in most events. The method is highly controllable because it can easily investigate the records from disaster and accident reports, and interview questions can be designed in a targeted manner. Relevant data based on realistic disasters and accidents are more representative, however, unlike quantitative measurements, they are often qualitative descriptions that lack accuracy and comprehensiveness. Although it is inexpensive to analyze specific reports and design interview questionnaires, inviting those people who have experienced emergencies to participate is a time-consuming task, and even some of them are reluctant to recall those incidents.

E. Determining the Research Gaps

1) Capturing Comprehensive Subgroup Data in Complex or Emergency Scenarios: On the one hand, most scenarios (e.g., single-exit rooms, corridors, and bottlenecks) chosen for crowd experiments are relatively simple, resulting in a significant lack of subgroup data in complex scenarios. This is mainly attributed to the fact that it is typically challenging for several specific cameras to cover the entire area of a complex scenario, and that calibrating and splicing the data collected by multiple cameras also takes a lot of time. Besides, human behaviors are more susceptible to environmental heterogeneity in complex scenarios, making their controllability and reproducibility inferior to those in simple scenarios [65]. On the other hand, subgroup data in emergency scenarios (e.g., fire, earthquake, and terrorist attack) are not comprehensive enough. Under natural conditions, the unpredictability of disasters and accidents leads to the inability to install data collection devices in advance, whereas factors such as smoke, jitter, and view angle probably cause interference in multiple aspects of the data collected by fixed cameras. Under controlled conditions, it is important to create an immersive sense of urgency while ensuring the safety of participants [18], but current crowd experiments are almost impossible to balance both simultaneously. Therefore, it is a critical task to capture comprehensive subgroup data in complex or emergency scenarios.

2) The Representativeness of Subgroup Data Acquired From Crowd Experiments Is Limited: Despite that experiments with human subjects can easily control various influence variables, the representativeness of subgroup data acquired from these experiments is often debatable. The main reasons are listed as follows: First, participants may exhibit unnatural behaviors in pre-designed scenarios under the influence of instructions or set conditions, that is, similar to achieving the experimental purpose by showing "intentional behaviors". Second, these participants in crowd experiments (e.g., students, teachers) are generally recruited from university campuses, and their physiology and psychology attributes tend to be distinctive, which may not reflect the heterogeneity characteristics of crowds in real life [80]. Third, subgroups are usually formed based on social relationships such as kinship, friendship, and collegiality, but participants in crowd experiments are in most cases arranged to be temporarily combined into subgroups, whether it would affect the experimental results is still unknown. From this, it is necessary to further verify the universality of research findings owing to the limited representativeness of subgroup data, and researchers also need to develop more advanced data collection methods to overcome this problem.

3) The Current Lack of Collection Methods for Obtaining Multifaceted Subgroup Data: Throughout the mainstream collection methods, the vast majority of them can merely capture pedestrian trajectories. Although this kind of data provides the basis for computing fundamental quantities (e.g., density, speed, and direction), it is not sufficient for further excavating the phenomena and behaviors of subgroups. Here are several inspirations, the gait data (e.g., step length, step frequency) extracted by tracking the alternating movement of two legs of pedestrians [81] are beneficial to explain the coordinated synchronization and evolutionary dynamics of subgroups, but related methods are mainly limited by accuracy, real time, and view angle. Using wearable collection devices [82], the motion data (e.g., acceleration, angular velocity, and body orientation) can be employed to precisely analyze the detailed features of subgroups during social interactions, however, equipment costs and experimental scenarios may impose certain constraints. The EEG signals of pedestrians captured by EEG systems [83] probably help to examine the dependence of motion perception on spatio-temporal relationships among subgroup members, but evoked modes and mental conditions all have strong impacts on the collected data. Thereby, these limitations make the current lack of available collection methods for extracting multifaceted subgroup data, which calls for dealing with this research gap as soon as possible to facilitate more findings of subgroup research.

IV. Analysis of Phenomena and Behaviors

The analysis of subgroup phenomena and behaviors is mainly concerned with detection and identification, explicit characteristics, social interactions, and evolutionary dynamics, which are discussed in terms of applicable scope, prior knowledge, research difficulties, and development potential, respectively. Furthermore, three research gaps in this aspect are identified below: (1) Inadequate public datasets and unified standards for validating subgroup-related algorithms. (2) The phenomena and behaviors of subgroups are seldom studied from a network science perspective. (3) Research on how subgroups affect self-organization phenomena is insufficient.

A. Detection and Identification

The detection and identification of subgroups in pedestrian and evacuation dynamics are critical for subsequent behavioral analysis and law exploration. Based on these definitions of subgroups by social psychologists [84], which include keywords such as organism collection [85], shared norms [86], self-categorization [87], and social identity [88], the current studies primarily focus on designing algorithms to detect and identify subgroups in pedestrian crowds.

The prevalence of surveillance cameras makes it a vital task to detect and identify subgroups from videos. A pioneering study suggested that subgroups may be identified by a set of rule-based procedures containing position, speed, and direction, but its accuracy requires to be improved [89]. With the rise of artificial intelligence, approaches related to computer vision have become mainstream. Based on the relationships of location and orientation among subgroup members, explicit motion models were proved to have high accuracy in subgroup identification by compound hypothesis testing [90]. The combination of trajectory clustering and feature learning was also used for subgroup detection, and numerical results showed relevant algorithms converge statistically with subjective human perception [39], [91]. Rising to the level of behavior, the walking strategies of subgroup members were found to cause coupled motion behaviors, whereby the structure similarity measure was employed to identify the common walking behaviors of neighboring pedestrians [92]. The subgroup features coupled with computer vision tasks (multi-target tracking and head pose estimation) [93] or semantic information (visual context) [94] could also be effective for subgroup detection in different crowd scenarios.

In addition to the above methods, mobile sensors and virtual reality techniques make subgroup detection and identification more simple. Since subgroup members tend to exhibit similar activity behaviors or movement patterns, the methods combining multiple sensors (e.g., Wi-Fi, accelerometer, and compass) with data fusion techniques improved the ability of subgroup detection [44], [95]. As a result of this, a variety of mobile sensing devices were employed to detect subgroup mobility levels and identify subgroup structure, and the high accuracy was demonstrated by comparing with real-life experimental results [45]. In a pioneering work on extracting subgroup characteristics using virtual reality techniques, a social interaction field model (SIFM) was proposed to predict the perceptual judgements of social groupings in given scenarios, making it possible to identify static and dynamic subgroups [67].

The detection and identification of subgroups are mainly studied for non-emergency situations, because the unpredictability of disasters and accidents leads to the lack of data and less relevant research in emergency situations. On the basis of combining the concepts in psychology and sociology, computer vision and machine learning techniques are mainly considered as prior knowledge. The difficulty of this research theme is how to validate the performance of relevant methods, as there is no standard or uniform definition of subgroups, and the crowd density may also affect human perception judgements [96]. In recent years, a large number of studies have been published in computer vision conferences and journals, and the development potential is worthy of expectation due to its importance in these fields such as neurocognition, public safety, and autonomous vehicles [67].

B. Explicit Characteristics

Whether manual, semi-automatic, or automatic methods are employed to identify subgroups, it is necessary to analyze the potential laws of explicit characteristics (e.g., subgroup size, spatial configuration, and walking speed). These studies not only reflect the local microscopic phenomena of subgroups, but also have guiding values for subgroup modeling.

The subgroup size is mainly dominated by a combination of social relations and environmental factors. Early studies based on field observations found the number of subgroups decreases sharply as the growing size, approximately following a (truncated) Poisson distribution and eventually reaching equilibrium [13], [97]. However, subsequent studies have shown that the distributions of subgroup size are largely altered by geographic or environmental influences. For example, special distributions with a higher proportion of dyad subgroups than isolated individuals were revealed by analyzing the videos of the admission test at the University of Milano-Bicocca [98] and the German Protestant Kirchentag at Dresden [99]. The discrepancies in the distribution of subgroup size in various public areas were found to be caused by different environments such as shop, travel, work, and study [35], [100].

The spatial configuration of subgroups refers to the shape features in space and has a significant effect on crowd dynamics. Subgroups of 2 to 4 persons were discovered to walk side by side at low densities, whereas "V"-like and "U"-like walking patterns might be formed at moderate densities due to social interactions [36]. At high densities, however, subgroup members affected by physical constraints would adjust their positions, resulting in a "river-like" spatial configuration [28]. For subgroups of 5 persons, three typical spatial configurations including "U"-like, 3-2 pattern, and 2-3 pattern were summarized by observations and experiments [101]. Large-scale datasets of pedestrian trajectories were also utilized to explore the intrinsic properties that affect subgroup dynamics, where the spatial configurations of subgroups containing 2 to 3 persons were dependent on environmental factors (e.g., density) and individual factors (e.g., purpose, relationship, gender, age, and body size) [43], [102], [103].

As another typical explicit characteristic, the walking speed of subgroups has been mentioned multiple times in related literature. Notably, most studies revealed a common conclusion: at low and moderate densities, the average walking speed of subgroups within 5 persons decreases with the increasing size and is lower than that of isolated pedestrians [36], [98], [104]. The proximity behavior of subgroups was discovered to slow the walking speed because subgroup members need to maintain spatial cohesion for communications [105], [106]. Researchers also focused on the walking speed of subgroups in various geographical areas or walking facilities. For instance, subgroups of more than 2 persons walk slower than pedestrians alone or in pairs when crossing roads in Jordan [107], the average speed of subgroups at signalized intersections decreases as the subgroup size increases [108], which also has a significant negative effect on the average walking speed on stairs [109].

The explicit characteristics of subgroups are largely within the scope of non-emergency studies, but a small number of studies in emergency situations are also involved. To explore the implied statistical laws, most prior knowledge concentrates on the statistical analysis of indicators such as the distribution, correlation, and significance level of data. The laws of explicit characteristics are often found in specific situations, whether they can be generalized to different environments is the key research difficulty. There seems to be an apparent convergence of research findings on certain aspects of explicit characteristics under conventional conditions [32], therefore, it appears difficult to reveal some subversive laws and needs further consideration under emergency conditions.

C. Social Interactions

It is challenging to figure out the interaction mechanisms behind the coordinated movement of subgroups. Intra-subgroup social interactions occur at the individual scale, while inter-subgroup social interactions with external individuals or environments take place at the larger group scale. This subsection reviews the literature regarding social interactions in both internal and external terms of subgroups.

Intra-subgroup social interactions reflect the underlying information about subgroup members, such as feature properties, social relationships, and hierarchical structures. Concerning feature properties, the spatial features of subgroups were noted as a trade-off between walking faster and facilitating social interactions [36]. The likelihood of judging the interacting subgroup depended on three distinct features: interpersonal distances, interpersonal angles, and avatar postures [67]. In terms of social relationships, a method was illustrated to infer implicit social relationships among pedestrians by using the anonymous trajectory data to derive observables involving interpersonal distance, group speed, speed difference, and height difference [110]. For hierarchical structures, crowds were found to form obvious subgroups of leader-follower hierarchy in high-building evacuations [61]. The other study demonstrated that the consensus reached in social interactions can determine the decisions of subgroups, which were made by leaders in almost half of the cases [58].

In scenarios like unidirectional flows, bidirectional flows, and bottleneck exits, inter-subgroup social interactions with external individuals or environments probably affect traffic organization phenomena. For unidirectional flows, subgroups were found to barely change the speed-density relationship at the macroscopic level, but strongly affect operational behaviors at the microscopic level [51]. The walking behavior of subgroups was reported to have a major influence on lane formation in bidirectional flows [50], such as reducing the number of lanes and making lanes broader [55]. The intrinsic cohesion of dyad subgroups also negatively affected traffic dynamics in unidirectional and bidirectional flow experiments of a ring-shaped corridor [54]. Concerning bottleneck exits, it was proved that there is no significant difference in evacuation time between individuals and subgroup members before leaving exits [56], and social interactions have almost no effect on time intervals when passing bottlenecks [111]. However, larger subgroups were shown to reduce the overall evacuation time due to the self-ordering effect near the exit [57].

The social interactions of subgroups are covered by both non-emergency and emergency studies. The research on intra-subgroup social interactions excavates potential information using prior knowledge such as statistical analysis and parameter inference, while studying the impact of inter-subgroup social interactions on macroscopic phenomena requires consideration of experimental design methods in crowd dynamics. With regard to this research theme, analyzing the mechanical mechanisms of interactions, extracting the expressions of interaction functions, and determining whether these precise expressions can be validated by empirical or experimental data are tough tasks [112]. Hence, social interactions are crucial for understanding how individual variables at the microscopic scale affect group behaviors at the macroscopic scale.

D. Evolutionary Dynamics

The evolutionary dynamics of subgroups primarily contain several actions such as maintaining, splitting, and merging. Maintaining is understood as the process by which subgroup members avoid separation due to cohesion effects, but splitting and merging may arise under certain circumstances such as obstacle avoidance and emergency evacuation. These actions of evolutionary dynamics depend to a large content on the influence of social relations and external environments.

For small-scale subgroups of 2-4 persons, they usually maintain unchanged in normal situations due to their strong group cohesion, but exceptions exist in emergency situations. Researchers found most small-scale subgroups have relatively "time-stable" and "universal" geometric structures [113], with most subgroup members staying close to maintain stability when encountering obstacles, and only a few splitting to avoid collisions [35]. Specifically, dyad subgroups are highly stable, triad subgroups frequently change in composition, tetrad subgroups vary little in formation, and the ratio of reorganization decreases as the crowd density increases [38]. Whereas small-scale subgroups are not always able to maintain stable states during emergencies. The splitting behaviors of dyad subgroups have been reported in evacuation experiments, in that weaker social bonds are easily broken under panics [61].

For large-scale subgroups of more than 4 persons, splitting and merging are prone to appearing in normal situations, but the opposite trend may occur in emergency situations. By analyzing data from field observations, large-scale subgroups were more likely to address complex assignments [114] and split into smaller subgroups around those who talk most [36]. Large-scale subgroups were easier to split than small-scale subgroups when facing obstacles, and reorganization occurred frequently as well [115]. Nevertheless, several empirical studies pointed out that the shared identity enhances the solidarity effect in emergency situations, making it easier for individuals or small-scale subgroups to combine into large-scale subgroups and maintain stability [79], [116].

The evolutionary dynamics of subgroups currently concentrate on non-emergency studies, but interesting evolutionary phenomena may also arise during evacuations. Relevant research requires prior knowledge from statistics to calculate the frequency and distribution of each action, and also advocates the use of mechanical analysis to explore underlying mechanisms of state transitions. The research difficulties are mainly related to two aspects: One is to extract and quantify the basic principles of subgroup evolution, and another is to study the evolution process of subgroups in emergency situations. This research theme has received a lot of attention in several fields [9], [117], while a few studies are found to be conducted in conjunction with other disciplines at present, whereby it has significant potential for development.

E. Determining the Research Gaps

1) Inadequate Public Datasets and Unified Standards for Validating Subgroup-Related Algorithms: The challenge of distinguishing subgroups from isolated pedestrians and the entire crowd has drawn a lot of attention in the field of computer vision. As far as current research is concerned, there are two main issues in validating subgroup-related algorithms: One is the lack of public datasets equipped with subgroup labels. Our survey shows that only a few studies have attempted to address this issue [118], [119], whereas the vast majority of datasets are labeled with independent pedestrians. Existing studies typically invite multiple coders to label subgroups in videos or datasets, but this is a time-consuming and laborious task. Considering that the criteria for judging subgroups vary from person to person, it is also questionable whether these subgroup labels are standardized and accurate. The other is the absence of unified standards formulated for algorithm validation. Most studies mainly depend on video-level labels (i.e., providing labels for the whole video) because this just needs to include which subgroups appear in the video without paying attention to the periods during which they are present. However, subgroup members may change dynamically (e.g., splitting, merging) as they move, in which case the subgroup labels should also be adjusted. Hence, it is worth discussing whether adopting frame-level labels (i.e., providing labels for each frame) as the standard is more rigorous. In conclusion, overcoming this research gap is expected to save expense costs and increase the persuasiveness of research results.

2) The Phenomena and Behaviors of Subgroups Are Seldom Studied From a Network Science Perspective: A host of disciplines are covered by network science, which concentrates on studying the commonality of various networks and universal processing methods [120]. Pedestrian and evacuation dynamics have always been highly correlated with network science, however, existing reviews suggest that most studies of subgroups are not effectively integrated with research findings from this domain. In fact, many concepts and knowledge in network science are perfectly feasible for further analyzing the phenomena and behaviors of subgroups. Let us give some examples, community detection methods can be referred to identify subgroups automatically, introducing the topological properties is beneficial to deeply explore the potential laws of explicit characteristics of subgroups, constructing interaction networks may help interpret the process by which behavioral changes propagate among subgroup members, and network evolution theories are conducive to further grasping the evolutionary dynamics of subgroups. Hence, performing the study of subgroups from a network science perspective is an exciting endeavor. Even so, due to many unsettled difficulties such as how the interactions between individuals can be quantitatively characterized as (weighted) network links [121], how higher-order structures (i.e., hypernetworks and simplicial complexes) can be used to explain subgroup interactions of three or more members [122], and how the dynamics and directionality of behavioral contagion can be effectively reflected in interaction networks [123], [124], this research gap leaves huge challenges and is hoped to be addressed in the future.

3) Research on How Subgroups Affect Self-Organization Phenomena Is Insufficient: Self-organization phenomena originating from non-linear interactions among pedestrians can produce various spatio-temporal patterns, which are not triggered by initial or boundary conditions, rules, and constraints [19]. Typical self-organization phenomena mainly include arching effects (i.e., crowds leave quickly at the exit or bottleneck and cause blockages with arch structures), lane formation (i.e., spontaneous separation flows triggered by oppositely moving pedestrians after a time period), oscillatory flows (i.e., bidirectional flows at the bottleneck characterized by oscillatory changes under certain densities), and stripe formation (i.e., multi-layer separations formed by the interpenetration of two intersecting pedestrian flows) [125]. The survey of existing studies shows that subgroups have been introduced into specific experimental scenarios (e.g., bottlenecks, unidirectional and bidirectional flows), but at the macroscopic level, they mainly concern the effects on fundamental diagrams and lane formation under conventional conditions [50], [51], [54], [55], and on the evacuation efficiency under emergency conditions [56], [111]. This leads us to know very little about how subgroups affect other typical self-organization phenomena in crowds. It is anticipated that filling this research gap may bring certain subversive findings to the study of self-organization phenomena and give rise to more targeted crowd control, such as possible differences in management strategies for various proportions or sizes of subgroups.

V. Modeling and Simulations

Crowd motion models have progressed toward macroscopic and microscopic aspects. Macroscopic models treat the moving crowd as a whole, but such models are rarely used due to the difficulty in describing various details of subgroups. In contrast, microscopic models focus more on the individual level, which is advantageous for modeling subgroups. Accordingly, this section reviews the publications related to social force models (SFMs), cellular automata models (CAMs), agent-based models (ABMs), and other approaches, and also summarizes the features of these models from scalability, simulation effects, verifiability, and computational complexity. Finally, three research gaps in this aspect are determined: (1) There is not yet a basic model with high generalizability for simulating subgroups. (2) The quantitative validation of subgroup models requires further attention. (3) Artificial intelligence techniques have not been notably reflected in subgroup models.

A. Social Force Models

In 1995, Helbing and Molnár [126] developed the initial version of the SFM to characterize the behaviors and interactions of pedestrian movements, and successfully simulated a lot of interesting self-organization phenomena. Following that, the escape panic version of the SFM was further proposed [127], which effectively reproduced the dynamical features of escape panic by taking panic psychology, herding effect, and social interactions into account. This model regards pedestrians as self-propelled particles, whose motion is described by the following Langevin equation:

$$m_i \frac{d\mathbf{v}_i(t)}{dt} = \mathbf{f}_{id} + \sum_{j(\neq i)} \mathbf{f}_{ij} + \sum_{W} \mathbf{f}_{iW} \tag{1}$$

Here, these forces on the right side of the equation collectively dominate the acceleration: the first term $\mathbf{f}_{id}$ is the self-driven force that motivates pedestrian i to move towards the destination, the second term $\mathbf{f}_{ij}$ is the interaction force between pedestrians i and j, and the third term $\mathbf{f}_{iW}$ is the interaction force between pedestrian i and wall W.

In recent years, researchers have made efforts in improving the SFM to simulate subgroup movements, which primarily characterize social interactions, cohesion effects, and leader-follower principles in the form of group forces. It is assumed that pedestrian i belongs to subgroup G, and the general equation of motion is expressed as follows:

$$m_i \frac{d\mathbf{v}_i(t)}{dt} = \mathbf{f}_{id} + \sum_{j\notin G} \mathbf{f}_{ij} + \sum_{W} \mathbf{f}_{iW} + \sum_{q\in G} \mathbf{f}_{iq}^{G} \tag{2}$$

On the basis of different theories, the group force $\mathbf{f}_{iq}^{G}$ has been described in various publications. The social interactions were used to construct the representation of the group force, and simulation results matched the walking patterns of subgroups in empirical observations [36]. By merging intra-subgroup coordination interactions with inter-subgroup avoidance interactions, researchers could reproduce subgroup behaviors that more closely resemble the observed phenomena [70], [128]. In terms of cohesion effects, the bonding forces [129] and attraction forces [46], [130], [131] between subgroup members were adopted to characterize the dynamics of consensus subgroups, and the associated numerical simulations indicated that the presence of subgroups affects walking behaviors and evacuation efficiency. For leader-follower principles based on social identity theories, the group cohesion generated by social relationships and the attraction of the leader to group members were combined to describe the group force [116], [132], [133], for simulating more realistic evacuation processes and investigating the effects of subgroups on evacuation performance. In addition, there are several studies considering different subgroup types to modify the SFM. For instance, the leader-centered model was shown to have less evacuation time than the group-centered model, whereas the opposite case occurred in the presence of multiple exits [134]. The model including three subgroup types of compliance, consensus, and outlier was effective in generating and performing high-density crowds in complex environments [135].

SFMs provide a great degree of flexibility in explaining subgroup mechanisms through mechanical expressions as they are continuous in the spatio-temporal dimension. This type of model reproduces both walking patterns and avoidance behaviors of subgroups in empirical observations, and simulates the effects of subgroups on traffic flows and evacuation processes. Part of SFMs are validated by reproducing empirical observations or comparing with experimental results. Finally, it should be emphasized that SFMs have relatively high complexity and will consume a large number of computational resources when dealing with large-scale crowd simulations [136].

B. Cellular Automata Models

The CAM was introduced by Von Neumann in the 1950s, and it has been gradually applied in the field of pedestrian and evacuation dynamics. The scenario is meshed in this model, and each individual updates its position in the cell based on the transition probability within a specific time step. Burstedde et al. [137] were the first to incorporate the floor fields into the expression of transition probability, where the static floor field presents the expectation of individuals to move along the shortest path to a destination and the dynamic floor field describes the herding behavior in response to the trails of other individuals. The transition probability is calculated by integrating a polynomial logic model as follows:

$$p_{ij} = N \exp\left(k_S S_{ij}\right) \exp\left(k_D D_{ij}\right) \left(1 - n_{ij}\right) \xi_{ij} \tag{3}$$

where N is a normalization factor satisfying $\sum_{i,j} p_{ij} = 1$, k_S and k_D are sensitivity parameters that adapt to static floor field S_{ij} and dynamic floor field D_{ij}. Besides, n_{ij} represents the occupancy parameter, and ξ_{ij} denotes the obstacle parameter.

To realize the modeling of subgroups, CAMs are primarily implemented by setting a series of local state update rules [27]. On the one hand, the existing laws of subgroup phenomena and behaviors are considered as influence factors. The spatial shapes of subgroups were defined by subgroup sizes or overlap rules, allowing the improved CAMs under subgroup conditions to examine the evacuation efficiency and provide guiding suggestions [100], [138]. The attractive effect arising from kinship behaviors was incorporated into the CAM to simulate interesting phenomena such as incoherence, jamming, gathering, backtracking, and waiting in the evacuation process [139]. Adaptive mechanisms for maintaining group cohesion were also supplied in CAMs to test the complex effects of subgroups on pedestrian dynamics in scenarios such as corridors, bends, and bottlenecks [140], [141], [142]. On the other hand, the behavioral characteristics of subgroups are incorporated into potentials or floor fields by establishing the coupling mechanisms. The internal attraction of subgroups and leader-follower principles were described by potentials, which allowed exploring the impacts of large-scale group behaviors, separation phenomena, and group formation on evacuation times [143], [144]. Besides, researchers combined subgroup interactions and leader-follower principles to improve the floor fields in CAMs, for replicating typical subgroup behaviors and investigating their implications on the passage efficiency and evacuation processes [145], [146], [147].

CAMs are discrete in the spatio-temporal dimension, and the scalability is mainly reflected in setting a series of local state update rules by considering the characteristics of subgroups. Such models can reveal the behavioral performance of subgroup movements, and the effects on pedestrian dynamics under conventional conditions and on evacuation processes under emergency conditions. Only a few studies have attempted performance validation by conducting controlled laboratory experiments [143] or calibrating model parameters [142], [146], while most ignore this procedure. CAMs achieve complex global phenomena by establishing simple local rules, which have substantial advantages of simple implementation and high computational efficiency [27].

C. Agent-Based Models

ABMs are built from the bottom-up structure, the system of which is modeled as a collection of autonomous decision-making entities. ABMs have been widely applied in human systems because they are noted to have significant advantages of capturing emergent phenomena, providing a natural description of the system, and flexibility [148]. In light of the complex interaction behaviors among individuals, most studies have also adopted ABMs within the scope of simulating the movement of subgroups.

ABMs generally take matrix-based, rule-based, attribute-based, and mechanism-based methods to characterize the subgroup behaviors, which makes the modeling of subgroups more flexible. For matrix-based methods, ABMs used the matrix to describe intra-subgroup structures and inter-subgroup relationships, and simulation results showed that subgroup sizes, internal structures, external relationships, and movement patterns all have impacts on crowd behaviors and evacuation processes [149], [150]. In rule-based methods, the rules of subgroup dynamics [151], following and avoidance [152], and conflict behaviors [153] were introduced to develop ABMs, and then the plausibility of these models in subgroup behaviors, collective movements, and collision prediction was verified in different test conditions. Regarding attribute-based methods, one proposed an ABM simplifying pedestrian features to attribute sets and combining adaptive mechanisms to maintain group cohesion, relevant simulations proved that this model can reproduce the phenomena associated with subgroup behaviors [154]. The cognitive, affective, and social decision-making attributes of subgroup leaders were also assigned to the ABM, and the average subgroup size was found to be the main factor influencing the evacuation process [155]. In terms of mechanism-based methods, the intra- and inter-subgroup avoidance mechanisms were quantified in ABMs to reproduce walking behaviors and avoidance patterns of subgroups [156], [157]. Another study added subgroup formation and mobility modes into the ABM to study the impact of subgroup behaviors on urban rail transportation evacuation times [158].

ABMs may be continuous or discrete in the spatio-temporal dimension, which have strong scalability [148] due to the fact that various flexible rules and mechanisms can be utilized to describe subgroups. The spatial structures, walking and avoidance behaviors, self-organization phenomena, and evacuation processes of subgroups can be successfully replicated by such models. Almost half of the studies adopt the data extracted from empirical observations and controlled laboratory experiments to verify the effectiveness of ABMs. Note that simulating the behaviors of the whole agents is a complex and time-consuming process, therefore, the computational complexity of ABMs is extremely high [22].

D. Other Approaches

Except for the three mainstream microscopic models listed above, researchers have sought to borrow concepts from other fields to model subgroups, including discrete element models (DEMs), game theoretic models (GTMs), deep learning (DL) and reinforcement learning (RL) techniques. These approaches are also undeniable components, which reveal the behavioral characteristics of subgroups from unique perspectives.

The basic principle of DEMs is to track the trajectory and rotation of each element in the system at a time step, and then calculate the interactions between elements and between elements and environments to update their positions. This model adopts the Hertz model to depict elastic contact forces between individuals, and also introduces rules for individual behaviors when they are not in touch. Considering the attraction of subgroup formation and the intra- and inter-subgroup interactions, a realistic simulation of subgroup behaviors was successfully achieved by the modified DEM [35], and it was found that the slower movement of subgroups would affect the escape efficiency in tsunami evacuation simulations [159].

Group dynamics are closely related to the process of dynamic games [160], in which participants examine and make decisions to dynamically alter their behaviors under the assumption of limited rationality. As a result, GTMs can be used to study the evolutionary patterns of subgroups, especially for cooperative behaviors. From the angle of rationality degree and social relationships, GTMs using Monte Carlo simulation methods were illustrated to explore the influence of subgroups on cooperative behaviors in evacuating crowds [161], [162]. Meanwhile, computational simulations conducted by the GTM based on subgroups revealed that both the ratio of subgroup members and the heterogeneous degree of preferences affect the collective behavior of evacuation processes [163].

DL allows computational models with multiple layers of data representation to conduct classification, recognition, and prediction [164]. RL addresses the problem of agent learning behavior through trial-and-error interaction with dynamic environments [165]. These methods learn crowd behaviors by training large amounts of data, and then the trained models for navigation or decision-making are combined with subgroup models. For example, a subgroup-based SFM was integrated with the multi-agent reinforcement learning (MARL) method to implement path selection and decision process [166]. Based on the multiagent framework of leader-follower and freedom modes, generative adversarial networks (GANs) were trained to obtain the evacuation path of the leader-agent [167].

These approaches are relatively less scalable than the aforementioned mainstream models. Among them, DEMs simulate the walking and evacuation behaviors of subgroups by adding crucial factors into the mechanical representation, GTMs consider the expression of network edges and game matrices to present the cooperative behaviors of subgroups, DL and RL techniques are primarily employed to realize the navigation and decision-making of subgroups. In terms of verifiability, DEMs are validated using video data, GTMs are hard to evaluate without psychological tests, DL and RL techniques verify training effects through test data. The computational complexity of DL and RL methods is much higher than that of DEMs or GTMs, requiring numerous computational resources in exchange for higher accuracy [168], [169].

E. Determining the Research Gaps

1) There Is Not Yet a Basic Model With High Generalizability for Simulating Subgroups: Most existing subgroup models are improved on the basis of mainstream microscopic models (i.e., SFMs, CAMs, and ABMs), implying the scarcity of a highly generalized basic model designed specifically for simulating subgroups. In practice, a crowd motion model with high generalizability has the following properties. First, it is supported by recognized facts or universal laws reflected in empirical investigations, media reports, video materials, and socio-psychological literature, such as the three force concepts in the initial version of the SFM [126] and the nine typical features in the escape panic version of the SFM [127]. Second, it should be equipped with clearly understood behavioral rules and relatively simple mathematical forms to flexibly extend the descriptions of individual attributes and environmental features, such as the movement rules and conflict resolution mechanisms for agents in CAMs, as well as the expression form of transition probability with floor fields integrated [137]. Given that subgroups are more complex than isolated pedestrians in terms of spatial configurations, movement patterns, and social interactions, it is not easy to extract crucial information for modeling. Meanwhile, establishing a pioneering subgroup model may require background knowledge from different disciplines, which also encourages interdisciplinary researchers to work together to fill this research gap.

2) The Quantitative Validation of Subgroup Models Requires Further Attention: It is a non-negligible undertaking to provide reliable validation means for subgroup models, which can help researchers analyze their simulation performance. The validation of crowd motion models is primarily divided into qualitative and quantitative aspects [170]: qualitative validations compare simulation effects with empirical observations to test whether the model is capable of reproducing certain phenomena or behaviors. In contrast, quantitative validations often adopt analytical metrics to evaluate the simulation results of the model. From the statistics of subgroup models reviewed in this paper, however, the validation procedures are only considered in no more than half of these studies, and even fewer involve quantitative validations. Although some studies claim that subgroup behaviors can be reproduced close to those in the real world, it is still doubtful whether these plausible qualitative validations are reliable. As a result, quantitative validations become the future tendency for evaluating subgroup models [171], and it is recommended to focus on the following three points: The first is the microscopic quantities inside subgroups (e.g., average distance, relative angle). The second is the macroscopic quantities outside subgroups (e.g., density, speed, flow, and order parameter of crowds). The third is emerging validation methods (e.g., based on virtual reality techniques, obtaining feedback from field data).

3) Artificial Intelligence Techniques Have Not Been Notably Reflected in Subgroup Models: With recent advances in artificial intelligence techniques, computer vision and machine learning offer desirable opportunities for crowd motion models [172]. However, little is known about how these techniques can be effectively integrated into subgroup models, which has not yet been translated to further progress in computer simulations. Regarding computer vision, existing research has made some breakthroughs in the detection and identification of subgroups. These achievements may provide new insights into parameter calibration and performance evaluation of subgroup models. For instance, the subgroup data extracted by automatic identification can be used as feedback for (approximate)-real-time adjustment of numerical simulations, even if it is exceedingly challenging to realize. Concerning machine learning, relevant methods are not often employed for modeling subgroups, but rather focus on the level of higher-order behaviors (e.g., path navigation, decision process). This combination fully utilizes the intuitive nature of models and the autonomous learning advantages of artificial intelligence. When the precise interactions between members and with other individuals or environments are difficult to extract, machine learning with data-driven methods will become a potential solution for constructing subgroup models. In conclusion, artificial intelligence techniques are expected to pave the way for a new phase of subgroup models and simulations.

VI. Applications and Solutions

The main purpose of studying subgroups is to serve applications and solutions such as crowd behavior analysis, evacuation planning, design solutions, and animation production. The research support, solution effectiveness, and application prospects of these aspects are analyzed as well. Following that, we ascertain three research gaps in this aspect as follows: (1) Subgroup factors are rarely embedded as options in crowd simulation softwares. (2) The effect of subgroups on crowd evacuation in emergency situations is controversial. (3) The achievements of subgroup research have not been effectively applied in swarm robotics.

A. Crowd Behavior Analysis

With the popularity of surveillance cameras in public places, crowd behavior analysis based on computer vision has become a hot topic of interest. Relevant studies involve the recognition, classification, and prediction of human behaviors, whereby the research findings of subgroups are mainly applied to pedestrian trajectory prediction and abnormal behavior detection.

Pedestrian trajectory prediction is crucial for analyzing the potential behaviors of subgroups. Taking the coherent motion patterns [173] or the social-aware information selection mechanism [174] into consideration, the improved long and short-term memory (LSTM) methods had advanced capabilities of trajectory prediction and interpretations of implicit social behaviors. The other study constructed a social behavior graph by recursively extracting social representations of subgroups [175], and great trajectory prediction results were attained by testing on standard datasets. Abnormal behavior detection is another significant application for analyzing crowd activities in surveillance videos. The automatic clustering method was developed to detect movement patterns of abnormal crowds based on pedestrian trajectory and subgroup information [176]. Besides, the interaction energy potentials method [177] and the joint temporal and spatial detection method [178] have been respectively proposed to detect abnormal activities of human subgroups, and evaluation results on public datasets demonstrated that these methods provide effective tools for early warning of crowd incidents.

The research support of crowd behavior analysis mainly contains the analysis of phenomena and behaviors for subgroups, in which behavioral patterns and motion features in social interactions are used for trajectory prediction, and robust findings in explicit characteristics serve for abnormal behavior detection. Many algorithms involving subgroups have been proven to achieve state-of-the-art performance for crowd behavior analysis based on public datasets. Relevant methods may be implemented into surveillance cameras or Internet of Things (IoT) devices to help rationalize crowd management, accident warning, and other tasks, which are important for the construction of smart cities [179].

B. Evacuation Planning

The management of crowds has long been a source of concern. Since the 21st century, crowd disasters have continued to occur all over the world, resulting in terrible deaths and injuries. To effectively reduce the likelihood of crowd disasters, the findings of subgroup research are particularly vital for formulating more reasonable evacuation planning.

There are certain differences in the effects of external influences on individuals and subgroups during evacuations. Subgroups were reported to have a negative impact on crowd evacuation in normal visibility but contribute to faster movements in low visibility, this provided new insights into the evacuation strategies under different levels of visibility [59], [180]. It was noted that subgroups have lower probabilities of signage detection and acceptance than individuals, this finding could be used to guide the design of emergency signage for more rational evacuation planning [62]. Regarding the influence of subgroups on evacuation processes, subgroups might delay or facilitate the egress time [56], [57], thereby evacuation planning needs to be considered in conjunction with actual situations. In complex scenarios, the social relationships of subgroups promoted the escape speed and interfered with the decision-making on selecting stairs or elevators, which were instructive for guiding evacuation planning in high buildings [60], [61]. Some researchers even provided a simulation platform called EPES to develop earthquake evacuation planning in urban outdoor scenarios by considering the formation and cohesion of evacuation subgroups [181].

The research support of evacuation planning includes two aspects: the analysis of phenomena and behaviors, together with modeling and simulations. The corresponding experiments and simulations can be employed to analyze the behaviors and impacts of subgroups in evacuations, which are valuable for developing reasonable evacuation strategies. Evacuation planning can improve the efficiency of crowd escape and reduce the number of casualties in emergency situations, its application prospects in the field of safety science will be expected because people are frequently influenced by families, friends, and colleagues during the evacuation process.

C. Design Solutions

The frequent gathering of crowds in public places makes the design solutions of environment layouts, building structures, and pedestrian facilities similar to artistic tasks, in that numerous factors such as traffic efficiency, comfort degree, safety level, and aesthetic appearance should be considered. In this case, studying subgroups is likely to help architectural designers to come up with innovative ideas.

When it comes to design solutions, the incorporation of subgroup factors may lead to more comprehensive schemes. According to field observations, the subgroup size was discovered to be an essential element in influencing pedestrian speed and spatial preference [182], [183], and it should be considered when addressing the spatial demands of pedestrian facilities. Another study collected pedestrian data at 18 selected locations in 5 Indian cities and indicated that the walking speed decreases with the increase of subgroup size and facility width, these findings could be used to guide the design of pedestrian facilities [184]. It was also strategic to examine the impact of spontaneously formed subgroups on pedestrian flows when assessing the level of service (LOS) for pedestrian facilities [185]. For specific walking facilities (e.g., stairs), researchers pointed out that different subgroup sizes on stairs probably develop diverse walking patterns [109], and also, both step time and step width of large subgroups raised significantly when descending stairs [186], which have valuable guiding implications for designing stair facilities.

Design solutions are generally supported by the analysis of phenomena and behaviors, such as explicit characteristics and social interactions. At present, subgroups play a less conspicuous role in the solution of building layouts and pedestrian facilities as they tend to be regarded as extra factors. This is attributed to that both individual factors (e.g., gender, age, race, and cultural preferences) and external factors (e.g., geographic location, climatic environment, and architectural style) might influence the design review [187]. Although there is no clear unified guiding standard for design solutions based on current studies, designing safer and more comfortable buildings or facilities remains a common vision for human society.

D. Animation Production

There are virtual crowds animated in a large number of movies and video games, and modeling crowd movements is therefore critical for the rendering of visual effects. It is necessary to consider frequent subgroups in reality during animation production, and subgroup behaviors such as interaction, avoidance, and navigation in virtual environments should also behave similarly to those in the real world.

Many academics have made attempts to improve the realism of subgroups for audiences and players. In the field of computer graphics, a flexible and effective approach was proposed by introducing the motion features of subgroups, allowing users to edit the subgroup motion as a whole [188]. Based on the hierarchy structure [189], communication behavior [190], and gaze behavior [191] of subgroups, related models were developed to simulate the movement of subgroups in virtual environments (e.g., train stations, parks, and airport terminals), and evaluation results showed that the behaviors of animated characters are more believable from the perspective of human observers. Moreover, a corpus-based approach for modeling dynamic crowd scenarios [192] and a pedestrian simulation and visualization system in urban environments [193] were vital for generating visually reasonable crowd animations and rapidly creating complex environments in animation industries. In addition, researchers also developed a psychophysics-based method to evaluate the perceived realism of behavioral features for virtual crowds, and the corresponding findings revealed that audiences have more perceptual flexibility when the frequency and density of subgroups increase [194].

The research of animation production is supported through the analysis of phenomena and behaviors, as well as modeling and simulations. The research achievements of subgroup phenomena and behaviors at the realistic level and subgroup models at the simulation level may contribute to the production of crowd animation. Subgroups have been shown to perform effectively in movies, virtual reality, video games, and other areas by the visual assessment of audiences or players. With the increasing demand for perceptual fidelity and immersive experiences in movies and video games [195], designing virtual crowds by incorporating subgroup factors in animation production is conducive for perfect visual experiences.

E. Determining the Research Gaps

1) Subgroup Factors Are Rarely Embedded as Options in Crowd Simulation Softwares: The vigorous development of crowd motion models has promoted the emergence of an increasing number of integrated crowd simulation softwares (e.g., Legion, STEPS, SimWalk, and PTV Viswalk) [29]. These softwares are able to create different types of virtual scenarios and environments, and simulate the movement behaviors of crowds based on CAMs or SFMs. With the corresponding visualization and analysis tools, they can help architectural designers, event organizers, and fire engineers to solve complex engineering problems. Despite that crowd simulation softwares allow users to directly define the characteristic attributes of virtual pedestrians (e.g., gender, age, height, speed, career, and mobility restriction), subgroup factors (e.g., proportion, size, spatial configuration, and social relationship) are often rarely taken into account, which contradicts the prevailing facts in the real world [32]. As a consequence, on the premise of utilizing software flexibility to develop virtual scenarios, crowd simulation softwares incorporating subgroup factors may give rise to more effective evaluation capabilities for environment layouts, building structures, and pedestrian facilities, and contribute to more valuable crowd control and evacuation schemes in complex environments.

2) The Impact of Subgroups on Crowd Evacuation in Emergency Situations Is Controversial: Under emergency circumstances, social relationships increase the likelihood of evacuation in the form of subgroups, even if complete strangers may also temporarily constitute subgroups. It is noteworthy that existing studies have shown controversial results on the impact of subgroups on crowd evacuation. In terms of crowd experiments, subgroups with longer responses and slower speeds were found to delay the evacuation time [56]; conversely, another experiment indicated that the self-ordering effect of subgroups near the exit significantly reduces the evacuation time [57]. In addition, factors such as visibility and evacuation signage were also shown to affect relevant findings [59], [109]. With regard to numerical simulations, the SFM-based subgroup model revealed that wider exits and larger subgroup sizes positively affect the overall evacuation [133]; however, another CAM-based subgroup model pointed out that subgroups have a negative impact on crowd evacuation, the degree of which grows with the increasing crowd density [146]. These differences suggest that a variety of individual and environmental factors would alter the conclusions about how subgroups affect crowd evacuation. This requires more rigorous findings derived from follow-up studies to provide relatively objective research bases for the formulation of evacuation planning.

3) The Achievements of Subgroup Research Have Not Been Effectively Applied in Swarm Robotics: Inspired by natural self-organizing systems, swarm robotics handle complex tasks in a cooperative manner based on local interaction rules [196]. Although centralization makes it easy to control swarm robotics, it also makes the system fragile and hard to scale. As an intermediate layer from individuals to groups, the hierarchical structure and leadership mechanism of subgroups have been indicated by relevant research. From this, researchers dealing with complex tasks through swarm robotics often use a divide-and-conquer approach to assign subtasks to robotic subgroups, and finally integrate them to achieve goals [197]. However, the dependencies and constraints between different subtasks may lead to a need for dynamic adjustment of the original assignment, while existing findings on social interactions and evolutionary dynamics of subgroups have not yet provided effective solutions for this purpose. Moreover, since it is by no means easy to program independent robotics to achieve coordinated actions of swarm robotics, the simulation and validation of subgroup models are currently hard to be done on swarm robotic platforms. Therefore, the achievements of subgroup research should be further utilized to help replicate complex behaviors in social systems and construct simulation systems of swarm robotics.

VII. Conclusion and Future Avenues

This paper provides a complete survey framework of subgroup research in pedestrian and evacuation dynamics, and presents a comprehensive review from four aspects: data collection and extraction, analysis of phenomena and behaviors, modeling and simulations, and applications and solutions. Based on current advancements, a series of research gaps in each aspect are made explicit to help researchers grasp the issues that need to be addressed. As a result, identifying future avenues is a critical step in narrowing the research gaps and producing valuable insights for subsequent studies.

1) Future Avenues for Data Collection and Extraction: First, emerging techniques can be adopted to collect subgroup data in complex or emergency scenarios. Ultra-WideBand (UWB) equipment has high transmission rate, low power consumption, and strong anti-interference capability. Compared with fixed cameras, it overcomes the shortcomings of crowd occlusion and insufficient coverage [198], making it possible to locate individuals in real time and acquire fairly accurate data in complex indoor environments. Besides, researchers may utilize virtual (or augmented) reality techniques to build different complex or emergency scenarios, and provide participants with immersive experiences to establish the interactions between players and virtual objects [199], from which subgroup data can be precisely captured. Second, more attention should be paid to the characteristics of environments and participants in crowd experiments. It may help to increase the realism and immersion of environments and reduce unnatural behaviors of participants by creating a sense of atmosphere in scenarios (e.g., smoke, fire, and alarms) and improving the effectiveness of instructions or rules (e.g., reward and punishment mechanisms tallying with sociopsychology). To enhance the representativeness of subgroup data, it is also required to consider the heterogeneity characteristics of subgroup members when inviting participants. Third, we probably solve the limitations of collection methods for obtaining multifaceted subgroup data from two directions: One is to select the collection devices by considering factors such as data accuracy, controllability, anti-interference capability, portability level, and expense cost. The other is to employ various data processing methods (e.g., interpolation, filtering, and denoising) to minimize errors and ensure the reliability of the collected subgroup data.

2) Future Avenues for Analysis of Phenomena and Behaviors: The first is to establish more convincing datasets with subgroup labels and determine unified validation standards. The former part can be realized by inviting anonymous coders on social networking platforms for manual judgements (e.g., questionnaire), with those on which the majority of coders reach consensus being regarded as correct subgroup labels. The latter part can be done by comparing the evaluation ability of validation standards to clarify under what conditions which standard is more reasonable for validating subgroup-related algorithms. The improvements of supervised and unsupervised methods [200], [201] on the automatic extraction of subgroup behaviors should also be a highlight when faced with labeled and unlabeled datasets in practical cases. The second is to analyze subgroups from a network science perspective. The pedestrian flow in a specific scenario can be viewed as a time-dependent network [202], with nodes indicating pedestrians and weighted links representing interactions. This transformation exactly corresponds human crowds to complex networks, which enables more concepts and knowledge (e.g., community, homophily) in network science to be referred for exploring the phenomena and behaviors of subgroups. The third is to design experiments and perform simulations on the subject of how subgroups affect self-organization phenomena in crowds. The possible research procedures are to first reproduce classical self-organization phenomena without considering subgroup factors, then gradually add subgroups and control relevant characteristic variables (e.g., proportion, size, and spatial configuration) in experiments or simulations, and finally qualitatively observe the influences (e.g., promotion, interference) produced by subgroups and quantitatively analyze the evaluation metrics (e.g., fundamental diagrams, Yamori's band index [203]), respectively.

3) Future Avenues for Modeling and Simulations: The modeling of subgroups can be developed following three strategies: One is to build highly generalized subgroup models inspired by the concepts, theories, and equations from other disciplines (e.g., particle physics [204]). The other is to develop bottom-up subgroup models from the angle of visual information processing (i.e., using low-order visual perception as input) [205], for overcoming the problem that most existing models assume a "birds-eye" perspective to have access to surrounding information. Last, utilizing machine learning to determine the explicit expressions of interaction functions in subgroup models from a large amount of data, and such models are often more accurate in describing the interaction characteristics of subgroups than those based purely on prefabricated functions [206]. The validation of subgroup models should take three other aspects into account: First, when quantitatively comparing simulation results with field observations or crowd experiments, microscopic and macroscopic quantities can respectively take probability density distributions and relationship curves as analytical metrics, with higher similarity implying better replicability of subgroup models [207]. Second, perhaps researchers could invite participants to observe subgroup characteristics in immersive virtual environments and analyze their assessments of simulation effects by questionnaire reports and statistical methods [70], which may be more reliable than simple self-qualitative validations. Third, computer vision can be used for obtaining feedback from the field to calibrate and validate subgroup models, which requires to be conducted in combination with the design of control systems (e.g., controllers, control objects, and detection devices) and improved towards (approximate)-real-time control effects.

4) Future Avenues for Applications and Solutions: First, subgroup factors can be treated as crucial points in updated versions of crowd simulation softwares. Owing to the fact that most existing softwares adopt SFMs or CAMs to simulate crowd motion, this allows relevant developers to conveniently select the improved subgroup models based on these two types of models and render various features in terms of visualization. These modules related to subgroups could be systematically made into plug-ins or patch packages and then incorporated into updated versions of these softwares, which help to provide more elaborate simulation results for subsequent applications and solutions. Second, we should ensure the rigor of research findings before formulating evacuation planning. Even minor changes in environmental features (e.g., scenario layout, emergency level, and risk type) may lead to differences in relevant conclusions, whereby detailed information and assumptions of environments should be clearly indicated. Moreover, subgroup features (e.g., proportion, size, and spatial configuration) cannot be constant settings, but should be considered under changing conditions. These concerns aim to avoid less rigorous conclusions such as "subgroups will promote crowd evacuation", and one should clarify "in what environmental features, subgroups with what features will promote crowd evacuation". Third, we encourage to conduct more experiments on human subgroups solving complex tasks, from which the interaction, coordination, and cooperation among intra- and inter-subgroup members can be deeply understood. Maybe related findings would provide new inspirations for swarm robotics to handle similar tasks. In addition, swarm robotics (e.g., E-puck [208]) probably become a better means for simulating and validating subgroup models, as they may achieve physical and material approximations to humans (e.g., wrapping rubber around the robotic surface to mimic human skin), which is more effective for reproducing the interaction forces between individuals.

Finally, it should be emphasized that the ubiquitous existence of subgroups in nature raises a host of open questions in different domains. Therefore, we call for more disciplines to focus on subgroup research as a subject. For international relations, various countries need to form alliances considering the interests of politics, military, economy, and culture [209], whether subgroups in international relations are beneficial to national development is an interesting question. In terms of astronomy, the size, density, velocity dispersion, and other features of subgroups in galaxy clusters [210], along with the evolutionary phenomena of grouping, merging, and survival [211], are essential for searching the origin of galaxies and exploring the mysteries of the universe. In the end, this paper is expected to help researchers grasp the latest achievements of subgroup research in pedestrian and evacuation dynamics, encourage them to bridge the research gaps between current advancements and future avenues, and offer new insights and inspirations for relevant research in a variety of fields.

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