Physical crowds and psychological crowds: Applying self-categorization theory to computer simulation of collective behaviour

Anne Mills Templeton

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School of Psychology

University of Sussex

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I hereby declare that this thesis has not been and will not be, submitted in whole or in part to another University for the award of any other degree.

Anne Templeton

Signature ………………………………………………………………………………

University of Sussex

Doctor of Philosophy in Psychology

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Summary

Computer models are used to simulate pedestrian behaviour for safety at mass events. Previous research has indicated differences between *physical* crowds of co-present individuals, and *psychological* crowds who mobilise collective behaviour through a shared social identity. This thesis aimed to examine the assumptions models use about crowds, conduct two studies of crowd movement to ascertain the behavioural signatures of psychological crowds, and implement these into a theoretically-driven model of crowd behaviour.

A systematic review of crowd modelling literature is presented which explores the assumptions about crowd behaviour being used in current models. This review demonstrates that models portray the crowd as either an identical mass with no inter-personal connections, unique individuals with no connections to others, or as small groups within a crowd. Thus, no models have incorporated the role of self-categorisation theory needed to simulate collective behaviour.

The empirical research in this thesis aimed to determine the behavioural effects of self-categorisation on pedestrian movement. Findings from a first study illustrate that, in comparison to a physical crowd, perception of shared social identities in the psychological crowd motivated participants to maintain close proximity with ingroup members through regulation of their speed and distance walked. A second study showed that collective self-

organisation seemed to be increased by the presence of an outgroup, causing ingroup members to tighten formation to avoid splitting up.

Finally, a computer model is presented which implements the quantified behavioural effects of self-categorisation found in the behavioural studies. A self-categorisation parameter is introduced to simulate ingroup members self-organising to remain together. This is compared to a physical crowd simulation with group identities absent. The results demonstrate that the self-categorisation parameter provides more accurate simulation of psychological crowd behaviour. Thus, it is argued that models should implement self-categorisation into simulations of psychological crowds to increase safety at mass events.

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I confess that I spent the majority of my undergraduate less focussed on the syllabus and more concerned with trying to remember what my shifts were that week and how to avoid being hit by shinty balls. I was interested in Psychology, but no topic truly enthused me and I constantly wondered about the practical implications of the research. Steve Reicher and Fergus Neville changed that completely. Steve, your wisdom inspired my interest in social psychology, and your support and generosity encouraged me to get involved in research. Fergus, you showed me how applicable crowd psychology is to real life. You very kindly invited me as a clumsy, confused undergraduate to the March for the Alternative protest. I remember looking around the protest and realising that I was set on the crowd psychology path for the long haul. Thank you both for all of the support that you gave me at St Andrews, and for all of the support you have provided since.

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Context statement

This thesis is organised in the new format style where chapters 2, 3, 4, and 5 are presented as papers for publication. However, in Chapter 1, I provide an overview of the thesis in the style similar to a traditional thesis introduction. The figures and tables are presented in numerical order across the thesis, and I have presented all references together in a single reference list at the end. Sections of Chapter 1 have been taken from two publications, Chapter 2 has been published, Chapter 3 is under review, and Chapters 4 and 5 have both been submitted for publication. I have included details about the publication status of each chapter in their title pages.

In Chapter 1, I have incorporated aspects from two publications on which I am second author. When discussing the Social Identity Model Application, I mention the main theoretical concepts that were incorporated into the computer model. Myself and the first author, Isabella von Sivers, co-designed the concepts for the computer model and its analysis, and co-wrote the paper with feedback from the other authors, Felix Künzner, Gerta Köster, John Drury, Andrew Philippides, Tobias Neckel, and Hans-Joachim Bungartz. My main contribution to this publication was providing the theoretical background for the model, which is the main element discussed in the chapter. In the first paragraph of the 'Methods and measures' section, I briefly address the potential difficulties of incorporating theoretical models into computer models. These concepts have been extracted from a publication by Michael Seitz, myself, John Drury, Gerta Köster, and Andrew Philippides. Michael Seitz and I collaboratively designed the ideas for the paper, and co-wrote it under the supervision of the other authors. For the publication, I lead and wrote the section on including theoretical criteria into a model, and co-wrote the section discussing model parameters with Michael Seitz. These are the points used in the chapter.

I am lead author of Chapters 2, 3, 4, and 5, followed by my academic supervisors, John Drury and Andrew Philippides. In all chapters, we collaboratively designed the ideas for the studies, I collected the data, conducted the analysis, and wrote the first draft of each paper, and look a lead role in writing the subsequent drafts. Both John Drury and Andy Philippides provided valuable feedback throughout the analysis and writing process. In Chapter 2, Gerta Köster, Michael Seitz, Isabella von Sivers, Felix Dietrich, and Benedikt Zönnchen were integral to affirming the typologies presented by providing helpful feedback from a computer science perspective. In Chapters 3 and 4, Michael Seitz and Andrew Philippides provided advice and practical support to build MATLAB software that would extract data from the footage for analysis. In Chapter 5, I present a computer model of collective behaviour with an underlying pedestrian model based on the Optimal Steps Model designed by Michael Seitz. Felix Dietrich, Michael Seitz, and Isabella von Sivers provided support to recreate a version of the Optimal Steps Model in MATLAB, which I adapted to incorporate aspects of self-categorisation theory. Andrew Philippides provided support to transfer the behaviour in the simulations into the data that I analysed.

Overview of research

Introduction

On 26th March, 2011, I participated in my first large-scale protest demonstration: ‘March for the Alternative’. On the way, the tube carriages were loaded with others going to the same demonstration. Their identity was evident by their placards, balloons, badges, and t-shirts with trade union logos on them. People would notice others with these same emblems and follow one another, merging into larger groups as they coordinated through the streets towards the starting point of the march. Other people who were not attending the march noticed this too; they navigated around the groups of people going to the protest, even walking on the road to avoid them. During the protest, there was a stark contrast between the behaviour of the crowd walking beside the protest and the crowd of people who were protesting. The people around the crowd navigated the pavement either as individuals to avoiding bumping into others, or moved together in pairs or small groups. The crowd on the pavement moved in different directions and at different speeds, but those participating in the protest were coordinated. Protesters chanted together, walked closely together, moved at a slower speed that was accessible to everyone, and were smiling despite being knocked into one another at times. In essence, the entire crowd of protestors seemed to move together as a group.

The coordinated movement of crowd members can be seen at numerous events, such as football fans entering and leaving stadiums, and attendees of music festivals and gigs. This behaviour differs from the crowd on the pavement where unconnected individuals or small groups were merely co-present in the same physical space, which can also be seen in crowds at shopping centres, or commuters at transport hubs. Accurate predictions of crowd behaviour are vital for increasing safety at mass events, yet there are key behavioural differences between these crowds which need to be understood to improve these predictions.

Computer models of crowd behaviour are a core method used for crowd safety by simulating crowd movement in to (ingress) and out of (egress) areas, movement within stadiums and other buildings, and planning emergency evacuations in these areas. Research on pedestrian dynamics has explored pedestrian movement, and crowd models have implemented these factors into models of collective behaviour to better predict and monitor movement at crowd events. These models are used to simulate a diverse range of crowds, from the movement of pedestrians in transport hubs (Burrows, 2015), to sporting events such as the Olympic Games (Owen, 2012). Despite this, computer models are typically based on very little research about what ‘collective behaviour’ is and how it emerges. Where collective behaviour in crowds has been investigated, modellers have often attempted to model animalistic traits such as ‘swarm’ behaviour (Chen & Lin, 2009; Parunak, Brooks, Brueckner, & Gupta, 2012), ‘stampedes’ (Cao, YangQuan, & Stuart, 2015), and ‘competitive’ parameters in evacuations (Ma, Li, Zhang, & Chen, 2017; Pan, Han, Dauber, & Law, 2007). As Sime (1985) indicates, other models often treat people as unthinking, predictable ‘ball-bearings’. These modelling approaches make advances towards simulating mechanical stepping behaviour in pedestrians, but they seldom explore underlying factors that may create collective behaviour. They do not address why an entire crowd may be motivated to coordinate their movement, such as the protesters at the March for the Alternative. One key aspect that these models neglect is how collective behaviour can emerge from psychological connections between crowd members.

Research from social psychology has focussed on the psychological underpinnings of what causes collective behaviour. Crucially, Reicher (2011) argues that there are important differences between *physical* crowds of unconnected people in the same place at the same time (such as those on the pavement trying to avoid the protesters), and *psychological* crowds whose collective behaviour occurs through a shared social identity (such as the protesters).

Self-categorisation theory (SCT: Turner, Hogg, Oakes, Reicher, & Wetherell, 1987) is a fundamental theory to explaining collective behaviour. Research on self-categorisation has shown how collective behaviour emerges through shared social identities and the perception of others as ingroup or outgroup members. For example, it has been used to explain how the perception of others as ingroup members motivates coordinated helping behaviour in emergency evacuations (Drury, Cocking, & Reicher, 2009a, 2009b), and safe egress of an outdoor music event (Drury, Novelli, & Stott, 2015). Despite crowd models simulating the behaviour of emergency evacuations and festivals, which social psychology has shown to consist of psychological crowds, the disciplines have only conducted limited collaboration to create a model of crowd behaviour that simulates pedestrian behaviour based on contemporary social psychological research of collective behaviour.

This thesis presents the first attempt to combine methodologies from pedestrian dynamics and computer modelling with contemporary theories from social psychology. To determine the effect of self-categorisation on pedestrian behaviour, I used methodology from social psychology to prime a *psychological* crowd with a shared social identity, and compared their movement to a naturally occurring *physical* crowd primarily comprised of the same people. Using methodology from pedestrian dynamics, I compared the walking speed, distance walked, and proximity between people in each crowd condition. I then extended this study to prime two large groups with different social identities and had them walk in counterflow to determine the influence of another group on speed, distance, and proximity compared to when the group walked alone. Finally, I present a computer model which demonstrates that models of physical crowd behaviour cannot simulate the coordinated behaviour of psychological crowds. In this model I introduce a new self-categorisation parameter and illustrate how attraction to ingroup members is needed to begin to simulate the micro-level collective movement of psychological crowds. I propose that future models of psychological crowds should incorporate a self-categorisation parameter to better simulate the behavioural differences of physical and psychological crowds.

In this chapter, I first provide an overview of research in pedestrian dynamics and argue that the current avenues of research that focus on individualistic traits, social and environmental cues, and small group behaviour are insufficient to explain the large-scale coordination of psychological crowds. I then demonstrate how computer models that implement crowds as consisting of either homogeneous masses, unconnected individuals, or small groups cannot model the collective behaviour of psychological crowds. Following this, I present theories of crowd behaviour from social psychology and propose that research into SCT provides valuable insight into the emergence of collective coordination in psychological crowds. In the ‘Methods and measures’ section, I set out the methodological strategy used in this thesis and explain the combination of methods that I have used from computer modelling and social psychology. Then, I provide a brief overview of the background and methods for each chapter in ‘Overview of chapters’, and the key results of each chapter and the overall research in ‘Summary of findings’. I then provide a discussion of the theoretical and practical importance of this research for both crowd modelling and social psychology in ‘Implications of findings’, and address potential limitations of this research and suggest avenues for future studies in ‘Limitations and future directions’. Finally, in ‘Conclusions’ I discuss the importance of incorporating the behavioural differences of physical and psychological crowds into computer models for event safety, and suggest that the inclusion of a self-categorisation parameter can be used to create more realistic simulations of the collective behaviour of psychological crowds at mass events.

Crowd movement in pedestrian dynamics

Research into pedestrian dynamics has aimed to increase the accuracy of computer models by exploring the factors that influence pedestrian movement and flow. These have been examined in three main areas: the effect of individual ‘traits’ on decision-making, the role of social and environmental cues on movement, and the influence of group behaviour on crowd flow. First, the individualist approach has examined how ‘traits’ influence behaviour in evacuation scenarios. For example, a computer experiment by Bode, Miller, O’Gorman, and Codling (2015) explored the role of altruism in evacuation behaviour, defined as the level of help provided to others. In this study, behaviour was compared between when there was no risk to the participants’ own safe evacuation if they provided help to others, and when a risk was posed to evacuating safely if help was provided. Bode et al. interpreted their results as suggesting that participants’ altruistic predispositions to help others decreased in an emergency situation, due to a compromise between helping another person and the risk of the participant evacuating safely. Other individualist approaches, such as research by Moussaïd and Trauernicht (2016), examined how personality types and incentives influenced helping behaviour. Here, participants in a virtual evacuation experiment were offered rewards or penalties for helping other people to evacuate safely, and then completed a questionnaire based on Murphy, Ackermann and Handgraff’s (2011) Social Value Orientation scale. Moussaïd and Trauernicht concluded that the level of helping provided in an emergency situation was influenced by people’s predisposition to compare receiving rewards against penalties to themselves if they helped others.

I argue that exploring the role of traits on evacuation behaviour reduces interactions between crowd members to people’s sum total of individual differences, and primarily focusses on ‘traits’ as a function of risk estimates rather than interactions between people. As yet, no research in pedestrian dynamics has ascertained which individual-level characteristics can explain collective behaviour in crowds. Individualist approaches neglect the findings from other research that indicate how group-level factors can influence crowd behaviour during evacuations. For example, a virtual reality experiment by Drury et al. (2009) found that group membership decreased individualist behaviour such as pushing and shoving. In this study, participants had to escape an underground railway in a mass emergency evacuation, and then complete a questionnaire about their identification with the group. The results implied that participants who most highly identified with the group exhibited the most cooperation with ingroup members and decreased competitive behaviour. Moreover, the research on individual traits implies that behaviour may be different in emergency evacuation scenarios and ordinary egress scenarios. However, the effect of social identity on coordinated egress has also been found in non-emergency events, such as the psychological crowd of attendees of an outdoor music event who collectively self-organised safe egress from Brighton beach with ingroup members (Drury et al., 2015). Thus, individualist accounts of behaviour bypass the fundamental effect that self-categorisation can have on collective behaviour.

A second area of research on pedestrian behaviour has examined the role of social and environmental cues on movement, such as the extent that evacuation times are influenced by how others in the area respond to an emergency evacuation alarm (Chow, 2007; Nilsson & Johansson, 2009), and where other pedestrians look in the environment (Gallup, Chong, & Couzin, 2012). In a series of controlled behavioural experiments and field observations of pedestrian zones, Moussaïd et al. (2009) explored the impact of other pedestrians on navigation choice to determine how pedestrians avoid collision with others. They found that pedestrian collision avoidance was a mutual interaction based on visual cues of which direction the opposing pedestrian moved, and concluded that coordinated evasion of other pedestrians is a mutual agreement based on social cues of others' direction. This area of research is a step towards researching how social cues can influence pedestrian navigation, but it examines fleeting interactions between individuals solely based on avoiding collision. It neglects how an entire crowd can self-organise behaviour for reasons other than collision avoidance based on their shared social identities, such as how the psychological crowd collectively self-organised egress from Brighton beach (Drury et al., 2015), or how pilgrims at the Hajj coordinated movement for complex religious rituals in high crowd densities and felt safe because they perceived themselves to be part of the same group (Alnabulsi & Drury, 2014).

The third area of research in pedestrian movement has examined how groups both influence, and are influenced by, crowd behaviour. Köster, Seitz, Treml, Hartmann, and Klein (2011) conducted a classroom evacuation experiment to determine how groups of varying sizes navigated a corridor together. They found that groups of three people walked abreast in low densities, but moved to a 'V' formation in higher densities to stay together. This was also found by Moussaid, Perozo, Garnier, Helbing, and Theraulaz (2010) when analysing footage of 1,500 pedestrian groups, but they further suggested that the group formation broke to allow faster movement through the crowd. Other research has extended this to show how pairs of pedestrians navigate counterflow and modulate their speed to remain close together (Crociani, Gorrini, Nishinari, & Bandini, 2016). This research made important contributions towards quantifying how pairs and small groups move within a crowd, but it reduced group behaviour to staying together to increase communication. Thus far, research in pedestrian dynamics is yet to extend past small group approaches. It does not address the underlying processes of why the groups are motivated to stay together, or how large crowds move together as a collective.

Approaches to crowd behaviour in computer modelling

The approaches that computer models use to simulate crowd behaviour can be grouped into three categories; crowds are portrayed as either a mass of people who act identically, individuals who act independently of everyone else, or interact in small groups of people with varying levels of social connections. In the first category, computer models which treat the crowds as an aggregate mass with identical characteristics have primarily been used to plan for emergency evacuations. Here, the influence of crowd size and density on movement has been explored, for example by analysing the effect of density on congestion in the crowd (Maury, Roudneff-Chupin, & Santambrogio, 2010), how pedestrian flow is affected by calculating the shortest distance to an exit (Zawidzki, Chraibi, & Nishinari, 2013), or how bottlenecks affect egress (Kabalan, Argoul, Jebrane, Cumunel, & Erlicher, 2016). These models are useful for planning evacuation routes and how crowd flow is influenced by avoidance of collision with obstacles or other pedestrians. They leave little room, however, for scenarios where groups interact within the crowd, or where the entire crowd self-organise to evacuate. In the second category, computer models rendered crowd members as unconnected individuals and provided pedestrians with unique features which influenced their behaviour, such as their health (Dou et al. 2014; Löhner, 2010), or level of competitiveness (Ma et al., 2017). This approach can increase the realism of simulations by adding more characteristics to the crowd, but they too assume that crowd members act as individuals and neglect the influence of group membership. Thus, they cannot account for how crowd members can behave as a group, or how the entire crowd can collectively self-organise.

In the third category, where modellers have included group behaviour, these models have been limited to small groups in the crowd with varying levels of social connections. This includes small groups who begin and leave the simulation together as an aggregate to determine the effect of groups on evacuation time (e.g. Idrees, Warner & Shah, 2014; Zheng et al., 2014), leader-follower modellers where ‘groups’ are comprised of a leader and the pedestrians who follow it (e.g. Crociani et al., 2016; Zhao, Zhong, & Cai, 2016), and models where pedestrians are grouped based on having similar properties (e.g. Musse & Thalmann, 1997; Pan et al., 2007). However, these approaches are still based on assumptions that the crowd is comprised of small groups of two to five people and do not incorporate the movement of larger groups.

Overall, these approaches to modelling have not addressed how large groups self-organise within the crowd, or how the entire crowd can behave as a group. Without incorporating the sense of ‘groupness’ from a shared identity, modellers cannot fully simulate the collective behaviour that research in social psychology has found in a plethora of crowd events. In recent years, there have been some attempts to base computer models on contemporary theories of collective behaviour from social psychology. For example, Singh et al. (2009) reference literature on SCT in their computer model of subgroup behaviour. However, this model focusses on small groups within a physical crowd, and does not implement any principles of SCT into an account of large-scale collective behaviour. One model that has attempted to incorporate the collective behaviour of groups in a psychological crowd based on principles of SCT, is the Social Identity Model Application (SIMA: von Sivers et al., 2016).

The SIMA model is based on research by Drury et al. (2009a), which examined accounts by survivors of behaviour during the July 7th 2005 London bombings. This research suggested that the shared danger created a social identity amongst survivors. Here, the crowd was characterised by delayed evacuation as the shared identities motivated helping behaviour and risk-taking for people who were previously strangers. To replicate this scenario, in the SIMA pedestrians were either modelled as healthy or injured so that they required help to evacuate. Crucially, SIMA implemented aspects of SCT by allocating each pedestrian the ability to have a social identity or not, and healthy pedestrians helped injured pedestrians to evacuate if they were ingroup members. Pedestrians who did not have a social identity immediately evacuated the train carriage. For those who shared a social identity, however, their target goal of evacuating was compromised by their target of providing aid to injured pedestrians, which resulted in longer evacuation time.

Von Sivers et al. (2016) present an important step towards modelling collective behaviour based on social psychological research. However, the original study by Drury et al. is based on self-report data due to the absence of footage of the evacuation, so the SIMA cannot be fully validated against the behaviour of the survivors. Quantified data of psychological crowd movement is still needed to accurately validate simulations of collective behaviour. This poses two problems for crowd modellers. First, they must ensure that the crowd they are basing their model on is a psychological crowd. Related to this is the second problem: to ensure a crowd is psychological, they must understand from where these psychological connections emerge, and use these principles to operationalise the theory into a computer model.

Social psychological theories of collective behaviour

Accounts of crowd psychology have attempted to explain collective behaviour as either innately anti-social, occurring through social facilitation, or through the emergence of norms in novel situations. In an account of the nature of crowds, Le Bon (1985/2002) portrayed the crowd as a 'primitive' entity, where entering the crowd was believed to release people's 'uncivilised' innate nature. Collective behaviour emerged through the crowd's innate susceptibility to suggestion and influence by others, where a person's individual self (and thus their accountability) was lost through submergence in the crowd. Here, 'contagion' through the crowd was said to occur as people succumbed to their unconscious anti-social instincts. This conception continued into Freud's (1921/1985) approach; being a member of a crowd unlocked people's unconscious and provided a place where they could throw off the constraints of socially acceptable behaviour and act according to their uncivilised impulses. Inherent in both Le Bon and Freud's theories is that that entering a crowd incurs a loss of ‘self’ and a descent into anti-social ‘primal’ instincts where collective behaviour is inherently anti-social. However, this approach neglects how crowds can collectively work together in a pro-social manner. For example, their approaches cannot explain the behaviour of the crowd members who shared water when others could not easily move due to high crowd density on Brighton beach (Drury et al., 2015), or how survivors of the 2005 London bombings stayed behind to apply first aid to injured people at a risk to their own safety (Drury et al., 2009a).

The individualist approach to crowd behaviour suggests that the collective is a nominal fallacy (Allport, 1924). Here, convergence theory proposes that crowds consist of numerous like-minded individuals in the same place, and collective behaviour stems from social facilitation where the crowd provides an environment to bring out attributes already present in those individuals. Individualist explanations, however, exclude how group-level factors influence behaviour, and do not address how normative behaviour is collectively established. Emergent Norm Theory (ENT: Turner & Killian, 1957) provides one account of how collective behaviour emerges through the generation of social norms. It suggests that crowd members look to others for cues about how to behave in the novel situation of the crowd environment. This is an important step towards incorporating communication and norms into collective behaviour, but only accounts for novel situations where norms were unestablished prior to the event. As Reicher (1982) indicates, crowds ordinarily come together for a reason and have pre-defined norms. ENT cannot explain pre-defined normative behaviour that spans numerous crowd events, such as chants used in multiple protest marches, fans performing Mexican waves at football games, or mosh-pits at festivals.

Two theories which can explain how connections between crowd members and social norms influence collective behaviour, are social identity theory (SIT: Tajfel & Turner, 1979) and SCT (Turner et al., 1987). SIT moves away from the portrayal of crowds as inherently anti-social masses, or individuals who happen to be in the same place at the same time. It suggests that people have a personal identity, which refers to their idiosyncratic differences from others, and social identities, which refer to their memberships in different social groups; and we understand our self-concept in terms of which identity is salient at a particular time (Turner, 1982). SCT suggests that when a particular social identity is salient, self-stereotyping causes individuals to define their self in terms of their identity as a member of that social group rather than their personal identity. Here, social identities become salient through the meta-contrast principle (Turner, 1991), where the salience of a group identity is influenced by members of the ingroup having fewer differences than the differences between their group and members of an outgroup. This leads to the depersonalisation process, where group members perceive themselves to be part of the same group and subsequently apply the group characterises and norms to themselves when that social identity is salient.

SCT explains how collective behaviour emerges as a group process, through categorising others as ingroup or outgroup members. The minimal group paradigm (Tajfel, Billig, Bundy, & Flament, 1971) indicates that social categorisation under seemingly arbitrary criteria for group membership is sufficient to evoke ingroup favouritism if the participants self-categorise themselves as being in the group (Grieve & Hogg, 1999; Hertel & Kerr, 2001). Research on SCT has demonstrated that even minimal group membership can influence how physically close people sit next to one another. Novelli, Drury, and Reicher (2010) used a minimal group manipulation to explore how group membership affected personal space. Minimal groups were created by having participants estimate the number of dots in a random pattern, and they were told the task was related to people’s cognitive differences. Following this, each participant was asked to place chairs in the room for other participants who were about to arrive. They were only given information about whether the other people coming had the same (ingroup) or different (outgroup) tendency as them to overestimate or underestimate the number of dots in the pattern. This group manipulation was sufficient to make participants place their chairs closer to ingroup members. Although this finding does not directly address collective behaviour, it indicates how proximity may be influenced by social identities and the perception of others as ingroup or outgroup members. This is an important consideration for computer simulations of crowd density that assume pedestrians avoid being close together, as it suggests that ingroup members will move more closely to one another than they would to others.

One way that people recognise shared group membership in others is through identity markers such as group emblems. For example, Levine, Prosser, Evans, and Reicher (2005) explored the role of social identity in helping behaviour using group logos to denote identities. In this paradigm, the identity of an injured confederate who needed assistance was manipulated by their shirt. In study one, participants were primed with a salient identity as Manchester United fans, and the confederate was altered to be perceived as either an ingroup member by wearing a football shirt of the team the participants supported, an outgroup member by wearing a football shirt of a rival football team, or an unbranded shirt in the control condition. Crucially, the confederate was more likely to receive help from participants when wearing the shirt from the ingroup condition. This research provided evidence that participants were more likely to approach and help people perceived to be ingroup, and that social identities can be both deciphered and operationalised through group emblems.

Importantly for crowd modelling, crowd behaviour can be influenced by the people’s social identities as a crowd member. SCT can explain, for example, why a crowd of football fans of one team may have social norms of acting violently and why a crowd of fans of another team with a different social identity will have a social norm of acting peacefully (Stott, Hutchison, & Drury, 2001). This also applies to crowds without a prior identity or social norms, such as the survivors of mass emergency disasters who became psychological crowds through their shared fate, and collectively self-organised safe evacuation based on their perception of others as ingroup members (Drury et al., 2009b).

Although studies have explored the effect of social identities on proximity and interactions between members of the same group, this is yet to be applied to an entire psychological crowd. The findings of Novelli et al. (2010) suggest that SCT could be a crucial aspect of understanding and modelling collective behaviour in crowds, as it implies that shared social identities influence people to be closer to ingroup members. Combined with research indicating that people can have social identities as a member of a crowd and perceive others in the crowd as ingroup members, this suggests that research in pedestrian dynamics and crowd models should explore the effects of SCT when an entire crowd share a social identity. The finding that ingroup members tend to move closer to one another than to outgroup members suggests that one avenue for research is how self-categorisation may motivate a crowd to maintain close proximity and how this impacts crowd movement.

The influence of social identities on collective behaviour suggests that crowd safety professionals should look to SCT when planning for psychological crowds. Research in pedestrian dynamics and computer models are one of the key tools used to plan for crowd behaviour, yet, with the exception of Sivers et al. (2016), they are yet to quantify and include how social identities and self-categorisation can influence collective behaviour. As such, the aim of this thesis is to quantify the behavioural differences between physical and psychological crowds, and use these to incorporate principles of self-categorisation into a computer model of psychological crowd behaviour, to improve simulations of collective behaviour for mass events.

Methods and measures

Methodological strategy

This thesis aims to combine methodology from social psychology, pedestrian dynamics, and computer modelling to a) determine how self-categorisation influences crowd behaviour and b) to replicate this by implementing aspects of SCT in a computer model. To measure the behavioural effects of self-categorisation, I compared the behaviour of a crowd of people walking when they did not share a social identity to when a shared social identity was salient. This necessitated a mixture of observational methodology to record the natural movement of a physical crowd, and a controlled experiment to prime the crowd to share a social identity. To create a computer model of psychological crowd behaviour, I used an existing model of physical crowd behaviour and implemented an additional self-categorisation parameter based on aspects of SCT. The self-categorisation parameter is validated by testing both versions of the model against the behaviour of the psychological crowd to determine which provides the best simulation of behaviour.

In this section, I first address barriers to implementing complex theoretical models into computer models. Following this, I discuss current methods from computer modelling to validate and operationalise models based on analysis of pedestrian dynamics from behavioural data of real crowd events. I address the computational challenges of modelling crowd behaviour, and I describe a pedestrian movement model that can simulate physical crowd behaviour. Finally, I provide an overview of group priming methods and measures of group identification from social psychology to ensure participants shared a social identity and that the behavioural effects of self-categorisation were measured.

Computer modelling methodology

One reason that computer modellers may not have incorporated aspects of SCT is due to the difficulty of creating models that can replicate complex social phenomena. Assuming a modeller understands the social identities and norms of the particular crowd being modelled, achieving a perfect replication of social norms, connections between individuals, and interactions with other crowds would require numerous model parameters. A high number of parameters incurs a heavy computational load that mean fewer scenarios can be simulated, particularly for mass events due to the large number of pedestrians. Moreover, the model would become increasingly untestable as the number of parameters increase; it would be difficult to determine where in the model the behaviour originated from.

The number of parameters provides a fundamental issue in modelling behaviour; however, from the perspective of social psychology it would be reductionist to exclude social identities as these are necessary to simulate the collective behaviour that exists in real psychological crowds. On one hand, macroscopic models which treat the crowd as a mass without interactions between individuals (e.g. Lei, Li, Gao, Hao, & Deng, 2012) would ignore how crowds self-organise between the individuals. On the other, microscopic models which focus on local interactions between individuals (e.g. Degond, Appart-Rolland, Moussaïd, Pettre, & Theraulaz, 2013) would exclude how self-categorising oneself as part of a group, and categorising others into outgroups, is crucial to explain collective behaviour. The model would also need to be tested against real crowds to ascertain how successfully it replicates the behaviour; yet, as Moussaïd and Nelson (2014) suggest, there is the potential to over fit a model so that it only becomes applicable to one scenario and therefore is not versatile enough for other events. Thus, a model of one group and their relevant social norms would not be able to capture the collective behaviour in other groups. Instead, a first step for modelling collective behaviour should be to determine the fundamental behavioural signatures that arise from shared social identities in pedestrian movement in psychological and physical crowds. By doing this, a parsimonious model can be created which has minimal parameters and can be applied to numerous mass events.

To model social identities in each pedestrian, and to allow social identities to motivate behaviour, inspiration is taken from the SIMA model (Sivers et al., 2016). The SIMA uses agent-based modelling which allows pedestrians (agents) to have individual attributes, goals, and cognition. In the SIMA model, pedestrians are allocated either a personal identity or a social identity. For those who share a social identity, pedestrian navigation is affected by helping nearby injured pedestrians to escape if they are ingroup members. One limitation of the SIMA, however, is that healthy and injured pedestrians evacuate together in pairs or triplets. Thus, although the model introduces social identity, it reduces the collective behaviour of the entire crowd to subgroups. The model I present increases the number of ingroup members to which pedestrians can orientate their behaviour, therefore allowing the entire crowd to coordinate as a group.

Another limitation of the SIMA model is that it is over fitted to the behaviour of the survivors of the 2005 London bombings. The model only explores the effect of social identities in one psychological crowd where people stay behind to help others if they share a social identity. This makes it difficult to apply to other crowd events. The issue of parsimony is addressed in the model I present by replicating the quantified micro-level movement of participants in Chapter 3 and 4: pedestrians who shared a group identity attempt to stay together, which affects their speed and distance. I argue that the regulation to maintain close proximity between ingroup members is a fundamental behavioural signature of how psychological crowds move and can therefore be applied to numerous crowd events.

A final criticism of SIMA is that it is not based on behavioural data. Computer models commonly use real pedestrian behaviour to operationalise movement and validate their models. For example, Moussaïd et al. (2010) used CCTV footage to analyse how group formations were influenced by high and low density crowds, and Vizzari, Manenti, Ohtsuka, and Shimura (2015) aimed to quantify how group sizes influenced evacuation by telling participants to walk in contraflow either as individuals, in pairs, groups of three, or groups of six. As such, in Chapters 3 and 4 of this thesis I primed participants to share a social identity and to perceive others as either ingroup or outgroup members, and I then use their behaviour to operationalise and validate the effects of self-categorisation in the computer model presented in Chapter 5.

When deciding which computer model of pedestrian behaviour to use as the basis for my simulations in Chapter 5, I first examined two main approaches that are used for modelling collective behaviour: social force models in continuous space and in cellular automata. Flow-based models broadly treat the crowd as Sime's (1985) ball-bearings example where pedestrians move on a non-discretised floor in continuous space and are navigated by attractive forces to a target, while repulsion forces guide them away from obstacles and other pedestrians. This approach requires high computational effort when simulating large crowds due to the number of calculations of attraction and repulsion in continuous space for each pedestrian, and can incur frequent overlapping of pedestrians (for an extended overview of the limitations, see Dietrich, Köster, Seitz, & von Sivers, 2014). Navigation in cellular automata is also guided by attraction and repulsion forces, but movement is based on floor-fields of discretised cells which pedestrians move between. The use of discretised cells requires less computational effort than the social force models, but navigation is limited to the shape of the cell, which decreases the acute pedestrian navigation required for large crowds who collectively regulate their behaviour.

The computer model presented in Chapter 5 uses the Optimal Steps Model (OSM: Seitz & Köster, 2012) as it provides acute navigation at a low computational load. As in the social force models and cellular automata, the OSM is based on attraction and repulsion forces where pedestrians are attracted to targets while being repulsed by other pedestrians and obstacles in the environment. The OSM overcomes the navigational limitations of cellula automata and high computational load of social forces by using a step-circle to influence steering. Here, realistic stepping behaviour in both dense and sparse crowds is achieved by allowing the pedestrian to move varying lengths on a step-circle around each pedestrian that dictates how many areas of the circle the pedestrian can move to.

I use analysis from computer modelling to explore the effect of self-categorisation on pedestrian behaviour. I measure the speed and distance walked based on research that explores the influence of groups on speed and movement during ingress and egress (e.g. Idrees et al., 2014; Zheng et al., 2014). Following from research on how small groups maintain formation in crowds (e.g. Köster et al., 2011; Moussaid et al., 2010), I analyse the proximity between group members by measuring the space around each pedestrian based on distance to their nearest neighbours. Thus, the model is used to simulate the speed of movement, distance walked, and proximity of pedestrians in physical and psychological crowds.

Methods from social psychology

Previous research exploring the effect of SCT on behaviour has primarily used controlled experiments (e.g. Novelli et al., 2010). This method allows behaviour to be measured in carefully controlled environments to ensure that the results are due to the manipulation of particular variables. Field observations have the benefit of analysing naturally occurring behaviour, but when introducing variables it can be difficult to decipher whether that particular variable affects behaviour or whether it is due to confounding variables. This thesis aims to quantify the behavioural differences of physical and psychological crowds to determine the effects of self-categorisation. Initially, I considered filming a type of crowd that prima facie evidence has suggested to be psychological (such as football fans entering a stadium), but this method was not chosen as it would pose two problems. First, although research on football fans has shown that they share a social identity, I would not be able to measure their level of identification with the group and therefore be sure that the behaviour was due to self-categorisation. Second, I would not be able to compare the behaviour of those people to when they walked in a physical crowd to determine the differences. Instead, I considered conducting experiments where participants were recruited to be in a physical crowd and then a psychological crowd which would have allowed manipulation checks and to ascertain levels of identification. This posed a particular difficulty, however, as testing participants for the physical crowd at the same time could create a shared identity through the shared task and therefore would not be measuring physical crowd behaviour.

Due to the limitations of both approaches, in Chapter 3, a compromise between a field observation and controlled experiment is adopted. First, a field observation was conducted to obtain footage of the physical crowd in a naturally occurring environment with limited influence on behaviour. Following this, I used experimental methods from social psychology to prime a social identity in the same participants and have them walk in the same area as a psychological crowd. This method allowed me to compare the behaviour of the pedestrians pre-manipulation and post-manipulation. Manipulation checks were not used in this study as it would have been difficult to provide questionnaires to the physical crowd without influencing their behaviour. However, in Chapter 4, manipulation checks were conducted on participants once they were primed to have salient social identities to ensure that they identified with ingroup members.

To determine the behavioural effects of self-categorisation, I needed to ensure that the pedestrians categorised themselves as being in the same group. As mentioned, the minimal group paradigm (Tajfel et al., 1971) indicates that social categorisation even under seemingly arbitrary criteria for group membership is sufficient to evoke (inter)group behaviour. Research by Reicher, Templeton, Neville, Ferrari, and Drury (2016) found that a university membership can be primed and used as a basis to operationalise group membership. Participants were primed to have either a local social identity as a student of their particular university, or a superordinate identity as a university student, by asking them to write down things that they liked about being a member of their allocated group. Results indicated that priming the participants to think about their membership of either a university or as a university student was enough to influence the perception of others based on their group status. Based on these results, in Chapter 3 group manipulation techniques and identity logos are used to prime participants to share a social identity based on their existing membership as Sussex Psychology students. The participants were informed that they were being selected to take part in the study because they were Sussex Psychology students, and were provided with caps with ‘Sussex Psychology’ logos on them to act as a further identity prime and ensure that participants were able to see who else was in their group. Notably, ‘Sussex Psychology’ was selected rather than ‘Sussex University’ to ensure that the participants identified with one another and not other people that they would come across while walking during the experiment who could also be Sussex University students. Following the use of minimal groups by Novelli et al. (2010), in Chapter 4 arbitrary team membership is used to create two groups with different social identities. Participants were randomly allocated into either team A or team B, were split into different locations, and were provided with either a black cap with a ‘A’ logo denoted on it, or a red cap with ‘B’ on it. Again, the hats ensured that participants could perceive the group membership of others.

Collective behaviour is dependent on self-categorising oneself as a member of the group, therefore manipulation checks on group identification based on Doosje, Ellemers and Spears (1995) were used in Chapter 4 to ensure that participants knew their group membership and to determine their level of identification with both their own group and the outgroup. Thus, the research in this thesis quantifies the behavioural differences between a physical crowd and a psychological crowd (Chapter 3), quantifies the behaviour of two large groups with different social identities in counterflow (Chapter 4), and incorporates principles of self-categorisation into a computer model of collective behaviour to simulate aspects of the behaviour found in these studies (Chapter 5).

Overview of chapters

In Chapter 2 of this thesis, I present a systematic review of 140 articles on computer models of crowds to establish the assumptions that modellers use about collective behaviour. Specifically, I critically examine the implicit and explicit assumptions held about ‘groups’ and ‘crowds’ that are incorporated into their models. Where the literature did not explicitly state their theoretical basis for crowd behaviour, I inferred it from how the crowd behaviour was modelled and any psychological literature that was referenced. It was found that the literature conceptualised the crowd in one of five ways; as a ‘homogeneous mass’, a ‘mass of individuals’, or consisting of ‘non-perceptual groups’, ‘perceptual groups’, or ‘cognitive groups’.

The most prominent models are the ‘homogeneous mass’ and the ‘mass of individuals’ approaches, and a trend analysis demonstrates that these have become increasingly popular in recent years. In the ‘homogeneous mass’ models, the crowd is seen as a large physical mass of pedestrians who have the same characteristics and act in the same manner. These models are primarily used to predict movement in evacuations based on collision avoidance and crowd densities (e.g. Fang, Lo, & Lu, 2003; Lee & Hughes, 2006). A critique of this design assumption, however, is that the connections between crowd members are limited to how they avoid collision with one another. In the ‘mass of individuals’ approach, granularity of crowd behaviour is increased by allocating individuals to have different properties, such as velocities or health status (e.g. Dou et al., 2014; Shi, Ren & Chen, 2009). Here, there is no connection between individuals at all, and therefore it is not suitable to model collective behaviour where pedestrians orientate their behaviour based on social connections between them.

The ‘non-perceptual groups’ subtype introduces small groups into the crowd for the purposes of determining the effect of groups on egress (e.g. Dogbe, 2012; Idrees et al., 2014). These groups, however, merely stay together throughout the simulation as an aggregate without any level of social cognition. The ‘perceptual groups’ subtype incorporates more complex dynamics between the pedestrians by having leader pedestrians who direct other follower pedestrians to the appropriate area in an evacuation (e.g. Moore, Flajšlik, Rosin, & Marshall, 2008; Qui & Hu, 2010). However, these treat group behaviour as a symptom of individuals following whichever leader is nearest at the time, and thus group structure is an antecedent of which leader is closest. The final approach, ‘cognitive groups’, model the most complex social groups of all the approaches. Here, a group is determined by which properties that agents share, and agents can seek out who matches their properties (e.g. Franca, Marietto & Steinberger, 2009).

Overall, Chapter 2 provides the first comprehensive review of crowd modelling literature since Sime’s (1985) review. It demonstrates that when this review was conducted, only the model by von Sivers, Templeton, Köster, Drury, and Philippides (2014) had incorporated aspects of social identity into a computer model to explain collective behaviour. I propose that to accurately simulate collective behaviour, computer models must include groups and the ability of individuals to be aware of their own social identity and the identity of others. To do this, I suggest that modellers should implement aspects of SCT to explain how crowd behaviour can be motivated by shared social identities.

Chapter 3 builds upon the systematic review by quantifying the behavioural differences between physical and psychological crowds on which to base a computer model of collective behaviour. I apply methodology from computer modelling to determine the differences in speed of movement, distance walked, and spatial proximity between a naturally occurring physical crowd, and a psychological crowd mainly comprised of the same people but who were primed to share a social identity. In the psychological crowd condition, I used minimal group manipulation from social psychology to prime the participants to share identities as Sussex Psychology students by using baseball caps with a ‘Sussex Psychology’ logo on them. Following the group manipulation, participants were instructed to walk along a path to the opposite side of campus. To ascertain the movement of the pedestrians, I used custom-made MATLAB software to map participants’ trajectories by tracking the positions of their heads as they walked through the footage. I then obtained their feet positions by transforming the coordinates of the head positions in the camera footage to a directly top-down planar view of the ground. The distance each participant walked was calculated by summing the distances between their coordinates, and their walking speed was calculated through their distance walked divided by the time they spent in the footage. The space between pedestrians was calculated using Sievers’s (2012) method for Voronoi decomposition which measures the space between pedestrians based on the distance between neighbours.

Using this analysis, I demonstrate that participants primed to share a social identity walked significantly slower and further, and in closer proximity than when the same people walked in the physical crowd condition. Moreover, Latent Growth Curve Analysis demonstrated that the psychological crowd maintained closer proximity with one another than any other groups or individuals regardless of the number of people around them. Finally, a prima facie exploration using cluster analysis indicated that the psychological crowd consisted of larger subgroups within the crowd that the physical crowd or the pedestrians who walked around the psychological crowd.

Based on this research, I provide quantified evidence of the behavioural differences between psychological and physical crowds. I propose that shared social identity motivated participants to attempt to remain together with ingroup members and that this caused them to collectively self-regulate their speed of movement and distance walked. Finally, I recommend that crowd safety professionals and crowd modellers should create plans for mass events that account for the behavioural differences between physical and psychological crowds.

In Chapter 4, I build upon the findings of Chapter 3 to quantify how the presence of another group with a different social identity affects the speed, distance and proximity of group members. Using a minimal group manipulation, I randomly allocated participants into arbitrary teams (team A or team B). Participants were given identity primes through hats that denoted their team membership, and were directed to different locations. Prior to walking, participants completed questionnaires which measured their level of affinity, bond, and commitment with members of their own team and the other team, taken from Doosje et al.'s (1995) measures of group identification. Results showed that members of both teams reported significantly higher levels of identification for ingroup members than for outgroup members.

To determine how the presence of another group influenced behaviour, I filmed team A when walking alone and measured their speed, distance, and proximity. Following this, team A and B walked in counterflow and their behaviour was measured again. Comparisons between team A when walking alone and team A when walking in the counterflow condition showed that participants significantly reduced their speed and distance walked to keep closer proximity with ingroup members and maintain formation as they walked against the other group. I used Latent Growth Curve Analysis to determine whether proximity between ingroup members changed in the presence of the outgroup, and found that the presence of an outgroup increased the proximity of the ingroup members so that they could maintain their group formation while waking in counterflow. Thus, in Chapter 4, I provide the first quantified evidence of how pedestrian behaviour is influenced by the presence of another group with a different social identity. I conclude by suggesting that crowd modellers should incorporate the behaviour of large groups in their models, including how groups regulate their speed, distance, and proximity in the presence of other groups.

Finally, in Chapter 5, I simulate the collective behaviour of psychological crowds by introducing aspects of SCT through a self-categorisation parameter into the OSM (Seitz & Köster, 2012). This is done through two versions of the model. First, a physical crowd is presented which simulates unconnected pedestrians with personal identities, and navigation is based on repulsion potentials to avoid collision between pedestrians. Second, a psychological crowd is simulated where pedestrians share a salient social identity and a self-categorisation parameter governs pedestrian navigation through attraction to ingroup members while navigating to a target location. The maintenance of close proximity with fellow ingroup members influences their speed and distance, so ultimately affects the length of time taken to reach their target. Crowd models commonly aim to replicate how the speed and distance walked is influenced by group formation. Thus, I validate the physical and psychological crowd models by comparing the speed, distance, and proximity produced in the simulations to the data of the participants from the physical and psychological crowds in Chapter 3. I demonstrate that aspects of psychological crowd behaviour can be replicated using the self-categorisation parameter, but that the physical crowd simulation cannot achieve the same behaviour. Overall, this chapter presents the first computer model that incorporates aspects of SCT to simulate the behavioural difference between physical and psychological crowds, and is validated against real crowd behaviour.

Summary of findings

The findings presented in this thesis provide evidence that self-categorisation caused key pedestrian behavioural differences in psychological crowds and large group behaviour. Specifically, I demonstrate that shared social identities cause crowd members to collectively self-regulate their speed of movement and distance walked to maintain close proximity with ingroup members. Therefore computer modellers should incorporate these behavioural signatures into their simulations of psychological crowd behaviour. In Chapter 2, I show that the crowd modelling literature uses inaccurate assumptions about crowds where the crowd is perceived to either be a mass who act identically, individuals who act independently of one another, or as consisting of small groups within a crowd with varying degrees of social complexity. Moreover, I indicate that in recent years, models which treat the crowd as either an identical mass or as individuals are becoming increasingly popular. As such, computer models to do not account for how large groups collectively self-organise based on their shared social identities, or even how an entire crowd can regulate their behaviour to move together.

In Chapter 3, through a field experiment I quantify the behavioural differences between physical crowds which are comprised of individuals and small groups, and psychological crowds where members perceive themselves to be in the same group. I demonstrated that categorising others as ingroup members caused pedestrians to maintain close proximity with one another as they walked. Moreover, the attempt to stay together influenced the speed and distance walked, indicating that the psychological crowd prioritised staying together over moving quickly. Based on these results, I argue that the key behavioural differences between physical and psychological crowds should be incorporated in crowd models to produce more accurate simulations of psychological crowd behaviour for the plethora of mass events that social psychology has shown to include psychological crowds, such as at sporting events, music festivals, and religious pilgrimages.

In Chapter 4, I build upon the results found in Chapter 3 to determine how large group behaviour is affected by the presence of another group with a different social identity. I demonstrate that when a large group walks alone the shared social identities cause them to regulate their speed and distance to remain close to ingroup members, but that these effects increase in the presence of an outgroup walking in contraflow. Specifically, the groups reduced their speed and walked less distance to enable them to remain close to ingroup members and maintain group formation to avoid the outgroup. I suggest that the behavioural effects caused by the proximity of an outgroup should be incorporated into models which simulate intergroup events, such as football fans entering or leaving a stadium, or crowds at a music festival with multiple stages.

Finally, in Chapter 5, I present the first computer model that implements aspects of SCT to replicate the collective behaviour of the pedestrians in Chapters 3. I present a model where self-categorisation motivates pedestrian movement through a desire to stay close to ingroup members and collectively regulate their behaviour to move together while reaching a target. This model is validated against the real behaviour of the physical and psychological crowds presented in Chapter 3. The model is proposed as a method for crowd modellers to introduce principles of SCT into simulations of crowd events to replicate aspects of how self-categorisation can motivate collective behaviour.

Overall, this thesis incorporates methodology from social psychology and crowd modelling to quantify the behavioural effects of self-categorisation on crowd behaviour and how this differs from that of physical crowds. Finally, it presents a computer model that incorporates some of the behavioural effects of self-categorisation to demonstrate how SCT can be implemented into crowd models to produce more realistic simulations of collective behaviour to increase safety at mass events. The findings presented in this thesis have theoretical and practical implications for both social psychology and crowd modelling, which are discussed below.

Implications of findings

Theoretical implications

The research presented in this thesis demonstrates the first attempt to incorporate SCT into computer modelling, and quantify the behavioural effects of self-categorisation on crowd movement. A review of the assumptions about crowd modelling had not been conducted since Sime (1985). As shown in Chapter 2, crowd modelling is becoming increasingly popular but the modelling literature uses outdated assumptions about the crowd as either acting identically, behaving as individuals without any interpersonal connections, or as only consisting of small groups and individuals.

This thesis also contributes to social psychology by quantifying the behavioural effects of self-categorisation in large groups and psychological crowds. Previous research in psychology has conceptualised that there are differences between physical and psychological crowds, and broadly explained collective behaviour in terms of group norms. I provide the first evidence that there are key behavioural differences between psychological and physical crowds at the fundamental movement level. I demonstrate that ingroup members regulated their speed of walking and distance walked to prioritise remaining in close proximity, and provide the first application of SCT to the pedestrian movement of crowds and large groups. Moreover, this research supports the findings of Novelli et al. (2010) that people will choose to be physically closer to people they perceive to be ingroup members. However, Novelli et al. were unable to determine whether the closer proximity was a result of preference for ingroup members or an attempt to be further from outgroup members. In Chapters 3 and 4, I ascertain that close proximity is a function of preference for ingroup members, but Chapter 4 demonstrates that this effect is increased by the presence of an outgroup.

Practical implications

This thesis provides quantified differences between physical and psychological crowds, and how group movement is influenced by the presence of an outgroup. Specifically, it first demonstrates that crowd modellers should incorporate principles from SCT to simulate how ingroup members prioritise walking together through the regulation of speed and distance walked. Second, it provides evidence that the effects of SCT are increased by the presence of an outgroup. In Chapter 5, I demonstrate how crowd modellers can implement principles of SCT into their models. I show that the close proximity of psychological crowds can be simulated by allocating pedestrians group identities, and having ingroup members be attracted to one another while using basic collision avoidance. I validate the model against the behaviour of a real psychological crowd where participants were primed to have social identities. Thus, I provide a computer model of collective behaviour that accurately captures the differences in proximity caused by self-categorisation, and propose that this should be used to better simulate collective behaviour to improve the safety of crowds at mass events.

I demonstrate that current computer models of crowds portray the crowd as either a mass who act identically, numerous individuals, or consisting of small groups within the crowd. Crucially, they do not account for the different behaviour of physical and psychological crowds. This thesis suggests that future plans and models for crowd safety should incorporate how self-categorisation influences pedestrians' use of space, and how this influences crowd flow. It provides evidence that people with a shared social identity appear to prioritise staying together rather than using space available, or walking at an optimal speed and distance. In particular, Chapter 4 demonstrates that ingroup members will move even closer together to avoid breaking formation when in the presence of another group even though this requires them to reduce their speed and impede crowd flow. Equally importantly, Chapter 3 shows that people surrounding a psychological crowd will walk further and more quickly in order to avoid walking into the crowd, rather than choosing the most optimal route to a target.

The behavioural differences of physical and psychological crowds outlined in this thesis are particularly important for crowd safety plans that make predictions regarding how pedestrians use space, avoid collision, and which factors influence their speed and distance during ingress and egress. These models often assume that pedestrians will spread out to maintain low crowd densities, choose optimal routes, and opt to increase crowd flow. This thesis, however, demonstrates that ingroup members may not use all of the space available when navigating through an area and instead prefer to be with ingroup members, that those around the psychological crowd will alter their trajectories to avoid entering it, and these decisions take priority over maintaining crowd flow.

Limitations and future directions

There are some potential limitations to this thesis: possible effects of group norms, confounds, non-independence of data, the generalisability of the findings to other crowd events, and the accuracy of the computer model. In Chapter 3, participants were primed to share a social identity as Sussex Psychology students using group manipulation and priming techniques that have been effective in previous research. One potential confound of this method is that there may have been norms specific to the social identity of ‘Sussex psychology students’ which influenced their walking behaviour; however, I am unaware of any such norms. Another potential confound is that the information sheets given to participants included the title of the study ‘Walking Together’, due to the title used in the ethical application. To limit any effect of this, participants were first given verbal instructions for the study that specifically did not mentioning walking together, were then presented with their information sheet and consent form, and the instructions were repeated verbally to emphasise focus on the spoken instructions rather than the information sheet. Both confounds are resolved in Chapter 4, as I used minimal group manipulation two create new identities of team A and team B, which did not have any pre-existing norms, and did not mention walking together in any of the material. Crucially, the same behaviour emerged in both Chapters 3 and

4, suggesting that the behaviour of participants in Chapter 3 was not due to any pre-existing norms or instructions to walk together.

Another potential limitation of Chapter 3 is that I did not measure participants' level of identification with the ingroup to ensure that the collective behaviour was due to self-categorisation. In Chapter 4, however, I used very similar group manipulation and priming techniques and further measured participants' strength of identification with both ingroup and outgroup members. The results showed that participants identified significantly more strongly with ingroup members than the outgroup, suggesting that the manipulation did work as intended. Crucially, the same regulation of behaviour occurred in Chapters 3 and 4, suggesting that the group manipulation and priming used in Chapter 3 was the cause of their behaviour. In Chapter 4, I did not provide physical crowd comparisons to analyse how the teams walked without manipulation, and did not obtain manipulation checks for a physical crowd condition to compare the levels of identification. There were three reasons that I did not include a physical crowd condition for Chapter 4. First, prior to recruitment for the manipulated scenario with team A and B, I did not know who would be taking part and so could not compare their footage prior to the study. Second, if I had filmed the participants walking in a physical crowd at a later date, it would have been difficult to find the people in the naturally occurring crowd, and it is unlikely they would have been walking with the same participants to allow a direct comparison of behaviour. Finally, a physical crowd comprised of different people in the same area would not have allowed a direct comparison between participants when their social identities were salient and when they were not.

A further two potential critiques of the design in Chapter 3 are that the data could be non-independent because the participants within the conditions affect one another, and the people walking around the participants were somewhat different in the two conditions. This is a particular difficulty of field studies; it is difficult to control the environment. I attempted to limit this by keeping the conditions as similar as possible. In Chapter 3, I argue that non-independence caused by pre-existing connections between participants is consistent across both conditions because they are primarily comprised of the same people. Moreover, I aimed to keep the number of people walking around the participants as similar as possible, and specifically explore the effect of number of people in the area. Due to the similarity of conditions, I suggest that the main difference is the presence of primed social identities.

A further potential limitation of this research is that, in Chapter 4, I could not compare each participant's behaviour with their corresponding self-reported level of identification with the ingroup and outgroup. Future research could match the behaviour of each participant with their reported level of identification, to investigate whether there is a relationship between the strength of ingroup identification and the strength of the behavioural effects.

Another potential limitation of this thesis is that I used an artificial crowd for the psychological crowd in Chapter 3, and artificial large groups in Chapter 4. As discussed in the Methods and Measures section, I chose this method to ensure that the participants were primed to share social identities. A pitfall of this is that it raises the issue of how representative and generalisable the findings are to other psychological crowds. Further studies are needed with different populations to explore whether these behavioural signatures occur across multiple crowd events. Future research could explore the behavioural effects of social identities in crowds that have been previously found to share social identities. For example, to determine how movement in physical crowds differs from psychological crowds of football fans leaving a stadium, protestors on a march, or at attendees at music festivals. Notably, if possible, these should be combined with manipulation checks to ensure that the crowds presumed to be psychological have a salient social identity and perceive other crowd members as ingroup.

Although ordinary psychological crowd events occur more frequently than emergency evacuations, computer models often aim to simulate pedestrian behaviour for emergency evacuations. Another possible limitation of this thesis is that we do not present a model of behaviour during an emergency evacuation. Due to the ethical considerations of simulating an emergency evacuation that could produce realistic behaviour a study of this nature is beyond the scope of this thesis[1]. Previous research in social psychology, however, has shown that the shared fate of emergency situations can evoke a shared social identity and cause people to coordinate with fellow group members to evacuate (e.g. Drury et al., 2009b). If footage could be obtained of behaviour in an emergency evacuation, future research could investigate whether the behavioural effects of self-categorisation found in this thesis occur in an emergency evacuation, and if so then how the choice to maintain close proximity instead of using optimal space affects evacuation egress.

There are potential limitations of the computer model presented in Chapter 5. Although the model can replicate the close proximity of ingroup members, the agents in the best version of the simulation walk further and more quickly than the participants in the psychological crowd from Chapter 3. The inclusion of the self-categorisation parameter makes a first step towards simulating the collective self-organisation of psychological crowds, but future models should alter the underlying pedestrian model to achieve the speed and distance of the real crowd. One solution could be to alter the number of potential directions on the step circle. This would allow direct forward stepping and create smoother trajectories, which would decrease the distance and speed walked. Additionally, to increase the reliability of the model presented in Chapter 5, future research could modify the size of the psychological crowd or the number of groups present in the area to determine how

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[1] Throughout the research presented in this thesis I have collected over 3 million data points, generated from both the crowd footage and computer simulations.

movement is affected. Finally, the participants in Chapters 3 and 4 walked along a path of 3.75 metres in width and attempted to remain on the path instead of moving onto the grass. Future studies could replicate the studies in a larger area to determine how ingroup members maintain proximity and avoid outgroup members when there is more space available to move in. This would provide data of different scenarios to validate the model against, which would enable the simulation of more diverse crowd events.

Conclusions

This thesis aimed to combine methodology from crowd psychology and computer modelling to quantify the behavioural differences between physical crowds of individuals and small groups, and psychological crowds where members of the crowd shared a social identity, and place these into a model of collective behaviour. The behavioural effects of social identity on crowd behaviour have been discussed since Reicher's (1984) analysis of the St Paul's riots, in which he states:

> The fascination of crowd psychology lies in the fact that it seeks to account for behaviour that shows clear social coherence - in the sense of a large amount of people acting in the same manner - despite the lack of either pre-planning or any structured design. (Reicher, 1984, p. 1).

This thesis presents the first attempt to identify the behavioural differences in psychological crowd movement caused by social identities and the categorisation of others as either ingroup or outgroup members.

The research presented in this thesis provides evidence that there are key behavioural differences between physical and psychological crowds, and suggests that crowd modellers should incorporate SCT into their models to better simulate collective behaviour. I demonstrate that social identities motivate ingroup members to maintain close proximity with one another while avoiding others, and that this influences their speed of movement and distance walked. Moreover, these effects are increased by the presence of an outgroup, causing ingroup members to move closer together to maintain group formation. I present a computer model that simulates aspects of the collective self-regulation of ingroup members to maintain close proximity by implementing a self-categorisation parameter. Here, agents are allocated social identities and navigation is influenced by attraction to ingroup members, causing agents to collectively self-organise with one another's movement to move together when reaching a target location.

Crowd modelling is being increasingly used to predict and monitor crowd behaviour to improve safety at mass events, yet I show that crowd models use incorrect and outdated assumptions about crowd behaviour and neglect the behavioural differences between physical and psychological crowds. Although crowd models are effective at predicting the behaviour of physical crowds, I demonstrate that psychological crowds prioritise being close to ingroup members, and this requires regulating their speed and distance to remain together. The distinctive behavioural signatures of psychological crowds suggest that current crowd models cannot accurately simulate their behaviour. This raises important questions about how well the models can plan for the safety of the psychological crowds. I present a computer model that incorporates aspects of SCT to simulate the close proximity of psychological crowds, and this is validated against real crowd behaviour. I propose that modellers should acknowledge the behavioural differences between physical and psychological crowds, and present a method to incorporate aspects of SCT into their simulations in order to increase the safety of people at mass events.

Chapter 2

Paper 1 - From mindless masses to small groups: Conceptualising collective behaviour in crowd modelling

Reference:

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Abstract

Computer simulations are increasingly used to monitor and predict behaviour at large crowd events, such as mass gatherings, festivals and evacuations. We critically examine the crowd modelling literature and call for future simulations of crowd behaviour to be based more closely on findings from current social psychological research. A systematic review was conducted on the crowd modelling literature (*N* = 140 articles) to identify the assumptions about crowd behaviour that modellers use in their simulations. Articles were coded according to the way in which crowd structure was modelled. It was found that two broad types are used: mass approaches and small group approaches. However, neither the mass nor the small group approaches can accurately simulate the large collective behaviour that has been found in extensive empirical research on crowd events. We argue that to model crowd behaviour realistically, simulations must use methods which allow crowd members to identify with each other, as suggested by SCT.

Introduction

Reconciling the gap: Crowd modelling and crowd psychology

Computer simulations are increasingly used to monitor and predict behaviour at large crowd events, such as mass gatherings, festivals, and evacuations. Recent approaches to crowd modelling have proved effective in explaining patterns in aggregates of people together in the same place, such as pedestrians in a busy street (e.g., Helbing, Molnar, Farkas, & Bolay, 2001; Moussaïd, Helbing, & Theraulaz, 2011) and small group behaviour within crowd flow (e.g., Köster et al., 2011; Moussaïd, Perozo, Garnier, Helbing, & Theraulaz, 2010; Singh et al., 2009). However, as yet, computer modellers have not created models which can adequately simulate certain key psychological features of large crowd behaviour.

In a commentary on collective behaviour, Turner (1987) argued that instead of treating crowds as individuals without any connections to one another, we need to explain the mental unity of real life crowds where the crowd behaves as one. As Reicher (1984) states, “the fascination of crowd psychology lies in the fact that it seeks to account for behaviour that shows clear social coherence—in the sense of a large amount of people acting in the same manner—despite the lack of either pre-planning or any structured design” (p. 1). There are numerous real world examples of such collective behaviour, for example football supporters performing a Mexican wave, protestors chanting together, or people coordinating their egress in emergencies. In each case, there is not only a physical crowd - an aggregate of individuals in the same location - but also a psychological crowd, that is, a shared psychological unity in those individuals and hence coordinated behaviour (Reicher & Drury, 2011). Indeed, in some crowd events there may be more than one large psychological group which exists within a physical crowd. For example, in the case of a football match, the fans of each team make up two psychological crowds that behave differently from each other within one large physical crowd of people in the same stadium.

For a number of years, researchers modelling crowd behaviour have recognized that to enhance the realism of simulations, and to better approximate collective behaviour, greater granularity or psychological detail is required (for examples see Galea, 2006; Gerodimos, 2006). Thus, some modellers have explicitly looked to the social sciences for both evidence and concepts for understanding collective behaviour (e.g., Franca et al., 2009; Fridman & Kaminka, 2007; Helbing, Farkas, & Vicsek, 2000; Johnson & Feinberg, 1997). In different ways, these and other modellers have argued that more accurate simulations will require the inclusion of *groups* within a crowd (e.g., Aguirre, El-Tawil, Best, Gill, & Fedorov, 2011; Bruno, Tosin, Tricerri, & Venuti, 2011; Singh et al., 2009). However, this raises the question of what is meant by the concept of 'group.' In both psychology and computer science there are different understandings of what is meant by a 'group.' Some of these understandings may be better than others in helping to produce a more realistic simulation of behaviour in a psychological crowd.

This article will critically examine existing crowd computer simulations by first outlining how understandings of group and collective behaviour have developed within social psychology, before presenting a systematic review of the implicit and explicit assumptions in modellers' treatment of 'groups' and 'crowds'. On the basis of this review we will argue that crowd modellers will benefit from incorporating aspects of SCT (Turner, 1982; Turner et al., 1987) in to their models in order to create realistic simulations of collective behaviour in line with findings from empirical psychological research.

Toward an understanding of collective behaviour

In early understandings of collective behaviour, crowds were treated as either a mass of people under one 'group mind,' or a mass of numerous unconnected individuals within the crowd. In 'group mind' accounts, crowds were understood as homogeneous entities where upon entering a crowd individuals lost both their individual ability to reason and their personality. Here every crowd member became indistinguishable from the others as they tended toward indiscriminate violence (Le Bon, 1985/2002). Individualist accounts, such as Allport (1924), argued that the idea of the collective is a nominal fallacy; groups and crowds are merely aggregates of individuals. Any collectivity was seen to occur only through social facilitation, whereby the presence of others stimulated behaviour that was already present in each individual. Later research demonstrated that neither group mind nor individualism could explain the social form of collective behaviour; the mechanisms posited by Le Bon, Allport and others to explain collectively were inherently primitive, irrational, and mindless. For both positions, collective behaviour tends to indiscriminate violence. However, extensive empirical research has shown that most crowds are not violent, and that even in riots and violent crowds, behaviour is rational, discriminate, and often shows a pattern which is in line with shared conceptions of legitimacy (e.g., Fogelson, 1971; Reicher, 1984, 1996; Reicher & Stott, 2011; Thompson, 1971).

In the current literature, collective behaviour is often characterised as ‘contagion’ where the mere sight or sound of others’ behaviour apparently influences individuals in a crowd to behave in the same way (e.g., Gallup et al., 2012; Mann, Faria, Sumpter, & Krause, 2013). However, social psychologists examining crowd behaviour have argued that the concept of ‘contagion’ cannot explain group boundaries to social influence. Thus, Milgram and Toch (1969) pointed out that a different model of collective behaviour was required to explain why the rousing effects of a demagogue affected the behaviour of protesters but not the riot police who were physically copresent in the same crowd. Psychological group boundaries in ‘contagion’ have also been demonstrated experimentally (van der Schalk et al., 2011).

Later interactionist approaches focused on group norms and interactions, and treated groups as psychological entities. Asch (1952) claimed that to understand the individual we must pay some attention to the group they belong to on the principle that the parts get their meaning from their relationship within the whole. Sherif (1967) proposed that being in a group has psychological consequences which are separate to those of the individual, and collectivity emerged when individuals had shared meanings and beliefs. The ideas of these and other Gestalt social psychologists were crucial for influencing psychological research to view individuals as members of a shared social field which was separate from them as individuals. Some sociologists began to take up this idea of interaction and applied it to crowds by focusing upon meaning-seeking and social norms for individuals to gauge acceptable behaviour in a novel situation where how to behave is not immediately obvious (Turner & Killian, 1957).

Other sociologists such as Aveni (1977) criticized previous research for treating crowds as “spatially proximate collections of individuals … undergoing some common experience” (p. 96) and also noted that previous research has paid little attention to the structure of crowds. Aveni’s criticism of this approach was followed by research looking at the affiliation between some members of the crowd. Various studies showed that in an evacuation people will attempt to remain with the small group that they have pre-existent affiliative bonds with, such as friends and family, even if this results in their evacuation time increasing or causing a hazard to themselves (Johnson, 1988; Mawson, 2005; Sime, 1983). However, approaches to crowd behaviour focusing on small groups fall short of explaining large collective behaviour. For example, these accounts cannot explain why in emergency situations a crowd of strangers can become united and help those who were previously strangers (Drury, 2012), or even that two large psychological crowds can exist who act together (intragroup) yet oppose one another (intergroup) (Reicher, 1996). Although there are many theories of crowd behaviour, such as the individualist and contagion approaches mentioned above, one of the most widely accepted and utilized accounts of collective behaviour in social psychology, which is grounded in extensive empirical research and can explain the collective behaviour of psychological crowds, is SCT (Turner, 1982; Turner et al., 1987).

The psychological crowd: A self-categorisation approach

SCT suggests that shared social identity - people's cognitive representation of their relationship to others - is what makes collective behaviour possible (Turner, 1985). SCT can therefore explain how physical aggregates of individuals can come together psychologically within a crowd and how a single physical crowd may consist of one, two (or more) psychological crowds who each act as a large group without prior interpersonal relationships or interpersonal interaction. SCT suggests that collective behaviour occurs through the process of *depersonalisation*. Here, individuals self-stereotype themselves in line with the definition of a social category and see themselves as being interchangeable with others in their social category. In doing this, individuals shift from their personal identity to their identity as a member of a particular social group (Turner et al., 1987).

A plethora of crowd phenomena has been explained by SCT, such as urban riots (Reicher, 1984), mass emergency evacuations (Drury et al., 2009a, 2009b), religious mass gatherings (Alnabulsi & Drury, 2014), music festivals (Neville & Reicher, 2011), and collective action (Drury, Reicher, & Stott, 2003). An example of this behaviour can be seen during the London bombings of July 7th 2005, where individual commuters became united through a shared identity in relation to the threat of the bombs. On the basis of their shared identity, the commuters helped each other and reported feelings of 'unity,' and felt 'part of a group' (Drury et al., 2009a, p. 81). The ability of SCT to explain behaviour in numerous situations indicates that modellers would benefit from applying this theory to their models in order to adequately simulate a broader variety of crowd behaviour.

Over the past decade, there has been an increased recognition among modellers that the concept of social identity is necessary for more realistic crowd simulations (for examples, see Aguirre et al., 2011; Köster et al., 2011; Langston, Masling, & Asmar, 2006; Smith et al., 2009). Here we examine whether any computer models of crowds have responded to this perceived need and adequately implemented a model of crowd behaviour in line with empirical research in crowd psychology. The following section will address the main modelling techniques that have been used to simulate crowds before we present the analysis of the conceptions of crowd behaviour found in the modelling literature.

Psychological requirements for modelling the crowd

Social psychological research on crowd psychology suggests a set of theoretical criteria that computer simulations of crowds should adhere to. In particular, a simulation must be able to model individuals who have the required perceptual and cognitive abilities to recognize identities - both their own and others'. Two commonly used approaches for simulating crowd behaviour are social force models and cellular automata. Both model types are typically based upon set rules and equations which have the same rules for every individual. In these models, the behaviour of individuals is determined by attraction and repulsion potentials such as attraction to an area in the virtual environment and repulsion from other individuals to avoid collision (e.g., Burstedde, Klauck, Schadschneider, & Zittartz, 2001; Zhang, Zhao, & Liu, 2009; Zhao, Yang, & Li, 2008).

Modelling techniques such as flow-based models which treat all members of the crowd as identical (e.g., Fang et al., 2003) are inappropriate as they cannot model the variable cognitive processes in individuals. However, other models such as agent-based models (ABMs) do have the potential to simulate these individual capacities as each agent can have different characteristics which affect their behaviour. ABMs can represent varying levels of perceptual and cognitive processes. Importantly, they are also dynamic, as the behaviour of the agents (people) within the crowd, their individual characteristics, and the 'information' that the agents receive, together drive their actions and can be updated at each time step of the simulation (e.g., Fang, Yuan, Wang, & Lo, 2008; Ji & Gao, 2007; Köster et al., 2011). ABMs thus lend themselves to modelling complex crowd behaviour and, in particular, situations in which individuals' characteristics alter as their social identities change during the simulation. They can also represent more complex abilities, specifically the ability of individuals to perceive their own group membership and the group membership of other agents in the simulation. For instance, membership has been used to alter agent behaviour through governing an agent's spatial location based on the perception of their own group membership and the group membership of others, such as in leader and follower models (e.g., Qiu & Hu, 2010; Yuan & Tan, 2007). As such, ABMS have the ability to simulate psychological components of group identity and self-categorisation in crowds. In this review, we will explore how the principles of identity and categorization have been implemented in existing ABMs and similar models of crowd behaviour.

Methodology

Reviewing the literature

A systematic review of the crowd modelling literature was conducted, in which publications were coded according to the psychological basis used to model crowd behaviour. Literature was sourced from the Science Direct database and Google Scholar search engine (see Figure 1). In order to locate the relevant literature, the search string of "crowd" was used. Articles and conference proceedings about crowd models were selected from the generated results. Publications recommended by Science Direct due to their similarity to the articles identified were also incorporated in to the collection, and the references cited in relevant literature were also used to source additional literature. Where the same articles were generated by both Science Direct and Google Scholar, the abstracts were read and incorporated into the corpus only once.

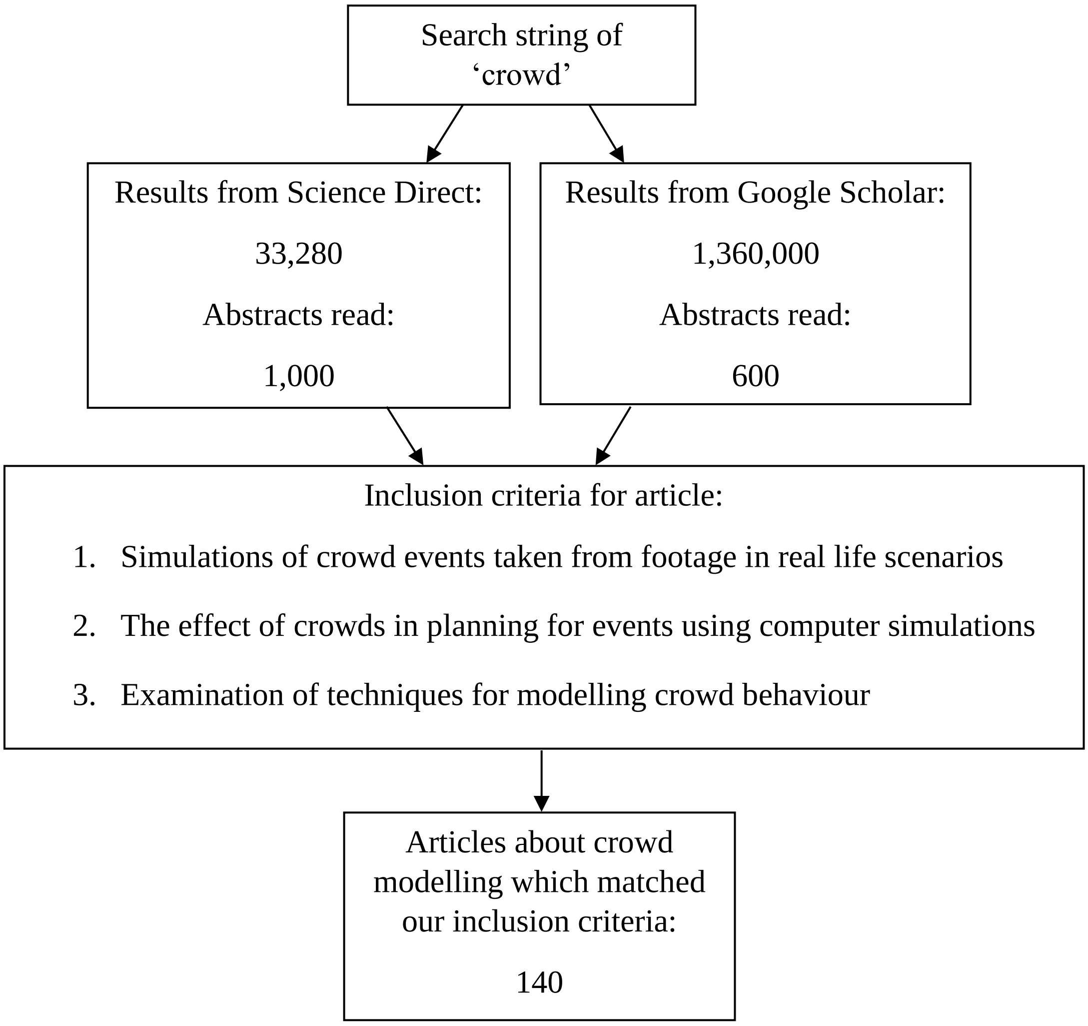

Figure 1. Search criteria and exclusion process for relevant articles.

Crowd modelling typology

Each article was analysed according to how the behaviour of the crowd was treated. Where the theoretical basis for the crowd behaviour being implemented was not explicitly stated by the authors, it was inferred from how the crowd behaviour was modelled and what psychological literature was referenced, if any. Throughout data collection, it became evident that in the literature the crowd was conceptualised and implemented in one of five possible subtypes. These subtypes fit in to two major types. In the first type, the crowd is treated as a *mass*. In the second type, the crowd is treated as consisting of a number of *small groups*.

The prima facie validity of the subtypes was established by presenting descriptions of each category (with examples) to an audience of crowd modellers. To ascertain that the reliability of the subtypes by the first coder were correct, an interrater reliability analysis was conducted on the scheme used to divide cases into types and subtypes. Fourteen articles were randomly selected, and for each article an excerpt was chosen which represented the approach taken toward crowd behaviour (minimum length of excerpt = 107 words, maximum length of excerpt = 341). These excerpts were presented to an independent judge, along with definitions of each subtype, and she assigned each article to a subtype. There was very good agreement between the allocation of the raters, Cohen's Kappa $\kappa = .90$ ($p < .001$) 95% CI (0.68, 1.00).

Results

The most prominent models were the *mass* approaches to crowd behaviour, which could be divided in to two subtypes; the '*homogeneous mass'* approach (52 articles) and the '*mass of individuals'* approach (31 articles). Within the *small groups* type, small groups are included in the crowd simulations but the understanding of 'groups' and methods to implement group behaviour varied. Thus there were three subtypes of small group simulations; '*non-perceptual groups*' (33 articles), '*perceptual groups*' (14 articles), '*cognitive groups*' (10 articles). The allocation of all models in to subtypes is shown in Table 1, and the number of articles in each subtype is shown in Figure 2.

Table 1

Authors of the crowd modelling literature and their respective subtypes

Authors	Year	Typology
Aguirre, El-Tawil, Best, Gill, & Federov	2011	Perceptual groups
Andrade, Blunsden, & Fisher	2006	Homogeneous mass
Banarjee, Grosan, & Abraham	2005	Homogeneous mass
Bandini, Gorrini, & Vizzari	2014	Perceptual groups
Bicho, Rodrigues, Musse, Jung, Paravisi, & Magalhaes	2012	Non-perceptual groups
Bierlaire, Antonini, & Weber	2003	Mass of individuals
Bodgi, Erlicher, & Argoul	2007	Homogeneous mass
Bruno, Tosin, Tricerri, & Venuti	2011	Homogeneous mass
Burstedde, Klauck, Schadschneider, & Zittarz	2001	Homogeneous mass
Carroll, Owen, & Hussein	2013	Homogeneous mass
Chen & Huang	2011	Non-perceptual groups
Chen & Lin	2009	Non-perceptual groups
Chen, Wang, Wu, Chen, Khan, Kolodziej, Tian, Huang, & Liu	2013	Perceptual groups
Cho & Kang	2014	Non-perceptual groups
Chong, Liu, Huang, & Badler	2014	Non-perceptual groups
Chow	2007	Homogeneous mass
Chrysostomou, Sirakoulis, & Gasteratos	2014	Non-perceptual groups
Davidich & Köster	2013	Mass of Individuals
Degond & Hua	2013	Homogeneous mass
Dogbe	2012	Non-perceptual groups
Dou, Chen, Chen, Chen, Deng, Zhang, Xi, & Wang	2014	Mass of Individuals
Fang, Lo, & Lu	2003	Homogeneous mass
Fang, Yuan, Wang, & Lo	2008	Homogeneous mass
Fienberg & Johnson	1995	Non-perceptual groups
Franca, Marietto, & Steinberger	2009	Cognitive groups

Authors	Year	Typology
Fridman & Kaminka	2007	Non-perceptual groups
Galea, Owen, & Lawrence	1996	Mass of individuals
Gawroński & Kulakowski	2011	Perceptual groups
Georgoudas, Kyriakos, Sirakoulis, & Andreadis	2010	Homogeneous mass
Goldenstein, Karavelas, Metaxas, Guibas, Aaron, & Goaswami	2001	Non-perceptual groups
Gutierrez, Frischer, Cerezo, Gomez, & Seron	2007	Mass of individuals
Haciomeroglu, Barut, Ozcan, & Sever	2013	Non-perceptual groups
Heïgeas, Luciani, Thollot, & Castagne	2003	Homogeneous mass
Helbing, Farkas, & Vicsek	2000	Homogeneous mass
Helbing, Farkas, Molnar, & Vicsek	2002	Homogeneous mass
Helbing, Johansson, & Al-Abideen	2007	Mass of Individuals
Helbing, Molnar, Farkar, & Bolay	2001	Non-perceptual groups
Heliövaara, Korhonen, Hostikka, & Ehtamo	2012	Homogeneous mass
Henein & White	2007	Homogeneous mass
Hu, Zheng, Wang, & Li	2013	Mass of individuals
Hughes	2000	Homogeneous mass
Hussain, Yatim, Hussain, & Yan	2011	Non-perceptual groups
Idrees, Warner, & Shah	2014	Non-perceptual groups
Ji & Gao	2007	Perceptual groups
Ji, Zhou, & Ran	2013	Homogeneous mass
Jiang, Xu, Mao, Li, Xia, & Wang	2010	Non-perceptual groups
Jiang, Zhang, Wong, & Liu	2010	Homogeneous mass
Ji-hua, Cheng-zhi, Zhi-Feng, & Bo	2013	Homogeneous mass
Johansson, Batty, Hayashi, Bar, Marcozzi, & Memish	2012	Mass of individuals
Johnson & Feinberg	1977	Perceptual groups
Johnson & Feinberg	1997	Perceptual groups
Johnson, Hart, & Hui	1999	Mass of individuals
Kamkarian & Hexmoor	2013	Mass of individuals

Authors	Year	Typology
Karni & Schmeidler	1986	Homogeneous mass
Khaleghi, Xu, Wang, Li, Lobos, Liu, & Son	2013	Homogeneous mass
Kirchner & Schadschneider	2002	Non-perceptual groups
Kirchner, Klüpfel, Nishinari, Schadschneider, & Schreckenberg	2003	Homogeneous mass
Köster, Seitz, Treml, Hartmann, & Klein	2011	Perceptual groups
Kountouriotis, Thomopoulos, & Papelis	2014	Perceptual groups
Krausz & Bauckhage	2012	Homogeneous mass
Lachapelle & Wolfram	2011	Non-perceptual groups
Langston, Masling, & Asmar	2006	Mass of individuals
Lee & Hughes	2006	Homogeneous mass
Lee & Hughes	2007	Homogeneous mass
Lei, Li, Gao, Hao, & Deng	2012	Mass of individuals
Li & Qin	2012	Homogeneous mass
Lister & Day	2012	Homogeneous mass
Lo, Fang, Lin, & Zhi	2004	Mass of individuals
Löhner	2010	Non-perceptual groups
Lozano, Morillo, Orduña, Cavero, & Vigueras	2009	Non-perceptual groups
Ma, Lo, Song, Wang, Zhang, & Liao	2013	Homogeneous mass
Ma & Song	2013	Perceptual groups
Manfredi, Vezzani, Calderara, & Cucchiara	2014	Non-perceptual groups
Marana, Velastin, Costa, & Lotufo	1998	Mass of individuals
Maury, Roudneff-Chupin, & Santambrogio	2010	Homogeneous mass
Mazzon, Tahir, & Cavallaro	2012	Mass of individuals
Mehran, Oyama, & Shah	2009	Non-perceptual groups
Mekni	2013	Cognitive groups
Moore, Flajšlik, Rosin, & Marshall	2008	Perceptual groups
Moussaïd, Helbing, & Theraulaz	2011	Mass of individuals

Authors	Year	Typology
Moussaïd, Perozo, Garnier, Helbing, & Theraulaz	2010	Non-perceptual groups
Mukovskiy, Slotine, & Giese	2013	Homogeneous mass
Musse & Thalmann	1997	Cognitive groups
Musse & Thalmann	2001	Cognitive groups
Musse, Babski, Çapın, & Thalmann	1998	Cognitive groups
Narain, Golas, Curtis, & Lin	2009	Homogeneous mass
Nilsson & Johansson	2009	Non-perceptual groups
Oğuz, Akaydın, Yılmaz, & Güdükbay	2010	Non-perceptual groups
Pan, Han, Dauber, & Law	2007	Cognitive groups
Parunak, Brooks, Brueckner, & Gupta	2012	Cognitive groups
Pelechano, Allbeck, & Badler	2007	Mass of Individuals
Pires	2005	Homogeneous mass
Qui & Hu	2010	Perceptual groups
Ramesh, Shanmughan, & Prabha	2014	Mass of individuals
Ran, Sun, & Gao	2014	Non-perceptual groups
Ryan, Denman, Fookes, & Sridharan	2014	Homogeneous mass
Sagun, Bouchlaghem, & Anumba	2011	Homogeneous mass
Sarmady, Haron, & Talib	2011	Homogeneous mass
Shao, Dong, & Tong	2013	Non-perceptual groups
Shendarkar, Vasudevan, Lee, & Son	2008	Perceptual groups
Shi, Ren, & Chen	2009	Mass of individuals
Shi, Zhong, Nong, He, Shi, & Feng	2012	Mass of individuals
Silverberg, Bierbaum, Sethna & Cohen	2013	Homogeneous mass
Singh, Arter, Dodd, Langston, Lester, & Drury	2009	Non-perceptual groups
Smith, James, Jones, Langston, Lester, & Drury	2009	Cognitive groups
Song, Gong, Cui, Fang, & Cao	2013	Mass of Individuals
Spieser & Davison	2009	Homogeneous mass
Tajima & Nagatani	2001	Homogeneous mass

Authors	Year	Typology
Thiel-Clemen, Köster, & Sarstedt	2011	Non-perceptual groups
Thompson & Marchant	1995	Non-perceptual groups
Tong & Cheng	2013	Mass of individuals
Varas, Cornejo, Mainemer, Toledo, Rogan, Munoz, & Valdivia	2007	Homogeneous mass
Vasudevan & Son	2011	Cognitive groups
Vigueras, Lozano, Orduña, & Grimaldo	2010	Homogeneous mass
Wagner & Agrawal	2014	Homogeneous mass
Wang, Li, Khaleghi, Xu, Lobos, Vo, Lien, Liu, & Son	2013	Homogeneous mass
Wang, Zhang, Cai, Zhang, & Ma	2013	Mass of individuals
Wang, Zheng, & Cheng	2012	Mass of individuals
Weifeng & Hai	2011	Mass of individuals
Wu & Radke	2014	Mass of individuals
Xiong, Cheng, Wu, Chen, Ou, & Xu	2012	Non-perceptual groups
Xiong, Lees, Cai, Zhou, & Low	2010	Homogeneous mass
Yamamoto, Kokubo, & Nishiniari	2007	Homogeneous mass
Yan, Tong, Hui, & Zongzhi	2012	Mass of Individuals
Yaseen, Al-Habaibeh, Su, & Otham	2013	Non-perceptual groups
Yu & Johansson	2007	Homogeneous mass
Yuan & Tan	2007	Cognitive groups
Yücel, Zanlungo, Ikeda, Miyashita, & Hagita	2013	Perceptual groups
Zanlungo	2007	Mass of individuals
Zanlungo, Ikeda, & Kanda	2012	Homogeneous mass
Zawidzki, Chraibi, & Nishinari	2013	Mass of Individuals
Zhang, Liu, Liu, & Zhao	2007	Homogeneous mass
Zhang, Liu, Wu, & Zhao	2007	Homogeneous mass
Zhang, Weng, Yuan, & Chen	2013	Mass of individuals
Zhao, Wang, Huang, Cui, Qui, & Wang	2014	Mass of individuals
Zhao, Yang, & Li	2008	Homogeneous mass

Authors	Year	Typology
Zheng & Cheng	2011	Non-perceptual groups
Zheng, Li, & Guan	2010	Homogeneous mass
Zheng, Sun, & Zhong	2010	Homogeneous mass
Zheng, Zhao, Cheng, Chen, Liu, & Wang	2014	Non-perceptual groups

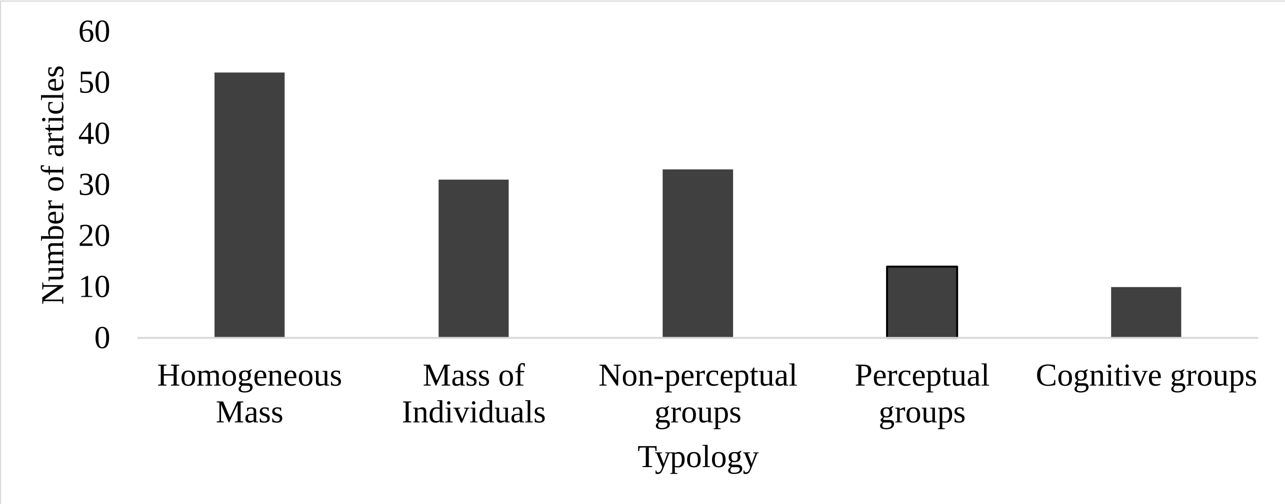

Figure 2. The number of articles published in journals and conference proceedings per subtype.

Mass crowd simulations

Simulations which fall in to this category treat crowds as consisting of numerous 'individuals' in a large mass. Despite research demonstrating that there are often small psychological groups within physical crowds and extensive research showing that collective behaviour requires individuals to see themselves as part of a large psychological crowd or group, groups are not implemented in these types of models.

'Homogeneous mass' subtype

The most commonly used approach within the crowd modelling literature is the *homogeneous mass* subtype. In examples of this subtype, the crowd is treated as an aggregate mass where every person is allocated identical properties. Within this subtype the crowd is regarded as a very large physical mass of individuals who coincidentally share the same goal - for example evacuating their environment. Literature in this subtype is therefore also characterised by modelling very basic agent behaviour, often simply avoiding collisions with one another. This approach is predominantly used in order to model the effect of crowd size and crowd density on egress in emergency evacuations and ordinary environments. For example, Fang et al. (2003) modelled a crowd flow pattern in an emergency situation to examine the effect of crowd density on the speed of evacuation. Similarly, to examine the effect of crowd size on the speed of egress, Lee and Hughes (2006) manipulated the size of the crowd and the complexity of the environment to determine the effect on pedestrian walking speed. Although the assumptions underlying this approach are adequate to model the movement of one crowd in a specific situation, these assumptions cannot accurately capture the behaviour of crowds in more complex scenarios, such as collective movement based on more than collision avoidance. When other crowds are introduced in to the model, modellers need to simulate different crowd movement and dynamic group identities. Thus, the assumptions of this subtype cannot be applied to other scenarios where there is more than one psychological crowd.

'Mass of individuals' subtype

The *mass of individuals* approach differs from the homogeneous mass approach in that agents are given unique properties which make them act as individuals within the crowd. Usually, individual differences are implemented in order to examine the factors that can affect evacuation egress. For example, Shi et al. (2012) assign individuals different attributes such as response time, walking speed, and endurance in order to create a more realistic simulation of pedestrian evacuation in a heterogeneous crowd in a metro station in China. Other example attributes include different pedestrian velocities or health status (e.g., Dou et al., 2014). As in the previous subtype, the crowd members act independently but with the same goal of evacuating as quickly as possible. Some models include elaborate environments which affect the egress of individuals in more realistic simulations; for example Shi, Ren, and Chen (2009) manipulate the egress time of individual agents by causing the agents to be affected by the level of smoke in the room and how injured the individuals are. However, although these models can become very intricate, the premise of the model is still that of individual behavioural differences within a 'mass', rather than acting as a collective.

'Small group' types

This subtype is characterised by small groups within the crowd. The small groups are usually implemented to determine the effect of groups on egress time, following Aveni's (1977) research that suggested that crowds may be comprised of small groups and individuals. The type of groups that are implemented varied and can be divided in to three subtypes on an ordinal scale of psychological realism. However, all of these models represent sociality merely in terms of relations within small groups where collective behaviour is reduced to being similar to interpersonal behaviour rather than the crowd being a group itself.

'Non-perceptual groups' subtype

Models of this subtype simulate physical groups but not psychological groups. That is, groups are implemented as homogeneous physical aggregates of people with no intragroup connection or individual knowledge of group membership. Instead, these are essentially small pre-existing groups, which physically stick together in the crowd regardless of the situation. Thus, they move as one homogeneous aggregate, as though they are one large and slow individual. Simulations which fell in to this subtype model small groups in order to investigate the effect of groups on egress, particularly at bottlenecks and exits (e.g., Idrees et al., 2014).

The implementation of small groups in this type of simulation is in some ways similar to the 'mass of individuals' approach. Instead of being an individual who acts independently within the mass, the group is an aggregate cluster of individuals which act as one within the crowd. Although no psychological connection between the groups is modelled, affiliative theories are often referenced (e.g., Aveni, 1977) to justify the inclusion of a group which stays together in a crowd situation (e.g., Feinberg & Johnson, 1995). For example, Dogbe (2012) modelled group behaviour using attraction and repulsion interactions, where social groups (assumed to be friends and family in this model) are attracted to move together throughout the simulation, but are repulsed by other neighbouring groups. By implementing group behaviour in this way, Dogbe is simulating a crowd where the groups are essentially small numbers of people clumped together within the crowd, with no meaningful interaction other than to change formation in order to stay together as they move throughout the crowd. Although it is an advance in terms of psychological theory used that these models simulate groups which are visible through their movement, the focus on small groups neglects the fact that groups can coincide and that an entire crowd can move together as a unit.

'Perceptual groups' subtype

In contrast to the non-perceptual groups subtype, in perceptual groups individuals are able to perceive their own group membership, the identity of others within the crowd, and act according to their role. Often models which fall in to this subtype include 'leaders' and 'followers' where followers are treated as being together as a group because of their connection to leaders as the simulation unfolds (e.g., Moore et al., 2008). Although in simulations of this subtype, individuals are able to perceive their own group membership and the group identity of other individuals, their movement is derived from the idea that people will come together as a group because they are looking for signs and information about how to act in a novel situation. This approach to group behaviour draws close parallels with ENT (Turner & Killian, 1957, 1987), as the agents are in a novel situation and look for leaders and social norms to discern how to act. However, a common problem with these models is that the agent's priority is to move to the nearest leader, which causes clusters of individuals to form groups without the individuals ever having a psychological bond with any other person (e.g., Qui & Hu, 2010). This could be criticized as these groups are based upon being in the same spatial location rather than being together because they share a group identity, and agents have no perception of others aside from avoiding collision and knowing who is a 'leader' or a 'follower.'

'Cognitive groups' subtype

In this subtype, individuals are able to perceive their own group membership and the group membership of others, just as in the 'perceptual' models. However, there is an extra component; individuals can share similar properties which are treated as 'cognition' by the authors. Here, agents who share the same properties are treated as being in a group. Additionally, the properties of each agent can change throughout the simulation, which causes the groups to change. As new information about the environment is given to the agents, the agents adapt their properties and seek out who they perceive to match their properties. Within this subtype, articles again tend to reference ENT to justify why they implement interaction between crowd members. For example, Franca et al. (2009) assign each agent certain properties. Here, when new information is introduced to the agents, the agents begin to communicate to establish new norms and they seek out others who share their properties or are affected in the same way by information, and consequently move into groups with agents who share the same properties as them.

The principles behind simulations of the 'cognitive' subtype are the closest to psychological realism and lend themselves to more diverse implementations of both group and individual behaviour. This approach is closest to SCT theory because it allows for the implementation of both individual properties and the ability to become a group member. It has also been used to simulate people acknowledging their group membership but being able to decide whether to act with their group or to act as an individual. Yuan and Tan (2007) created a scenario where a crowd of people have to evacuate a room, but agents can decide whether to leave with their group members or not. Moreover, this subtype focuses on the fact that groups exist based on shared properties, which is theoretically in line with the proposal of SCT that groups exist due to a sense of commonality between their members.

Trend analysis

As Figure 3 shows, although the initial models of crowd behaviour began with a mix of articles from all subtypes, since 2007 the '*homogeneous mass*', '*mass of individuals*' and '*non-perceptual*' subtypes have been more prominent. Although there was an initial spike of articles in the '*cognitive groups'* subtype in 2001, then another in 2009, this subtype has largely been overtaken by the 'mass' approaches. One factor which could have contributed to the rise in crowd modelling articles over the years is increased access to crowd modelling software. The upsurge of crowd simulations - particularly in the 'homogeneous mass', 'mass of individuals' and 'non-perceptual groups' subtypes - over the last decade could be due to the availability of modelling software such as SIMULEX (e.g., see Thompson & Marchant, 1995) and FIREScape (e.g., see Feinberg & Johnson, 1995), which provide tools to simulate crowds without focusing on group behaviour (for a detailed analysis of emergency evacuation simulation models, see Santos & Aguirre, 2004).

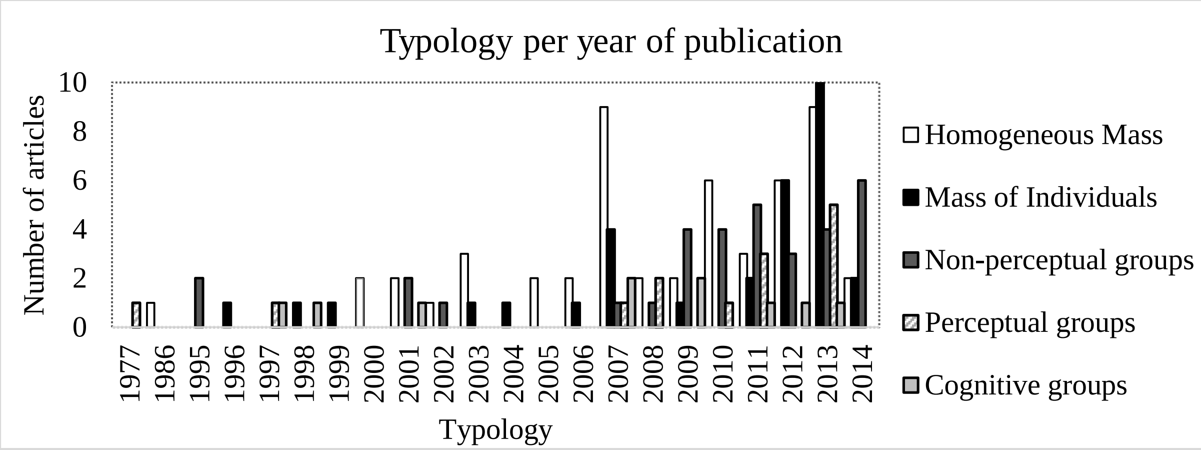

Figure 3: Prevalence of subtype per year of publication.

Discussion

Misrepresenting the crowd

This review has discerned that a plethora of models of crowd behaviour have successfully simulated crowds of individuals. Notably, the majority of models have not aimed to incorporate psychological theories in to their rationale for crowd behaviour. However, to accurately monitor and predict the collective behaviour exhibited in psychological crowds specifically, it is imperative that models being used for crowd safety management have an accurate understanding of collective behaviour taken from empirical research. In line with what is known in crowd psychology, a realistic model of collective behaviour must include the capacity to simulate the difference between physical crowds and psychological crowds. Specifically, it must be able to model both the members of a crowd categorising themselves as individuals distinct from other individuals, and the situation where the same individuals categorise themselves as members of the crowd and hence share an identity. Simulations of psychological crowds must therefore address the way in which people can identify with one another and how collective behaviour emerges from this process.

This review has found that some crowd modellers have begun to approach psychological realism by incorporating groupness (e.g., Aguirre et al., 2011; Moore et al., 2008) in their models of crowd behaviour, particularly those we denoted as the '*cognitive* *groups'* subtype. However, these developments have not occurred at the same rate. Over the previous decade, there has been an increase in models which have implemented the 'homogeneous mass', 'mass of individuals' and 'non-perceptual group' approaches. The advantages and limitations of each subtype will be discussed, and we propose the theoretical advances that must be made in order for crowd models to simulate collective behaviour more accurately across a variety of collective behaviour scenarios.

Constructing the relationship between the individual and the group

Examples of the mass type of model support Sime's (1985) assertion that in computer simulations people are treated as ball-bearings; they are unthinking and act at a very base level of simply moving without interacting with one another. The *homogeneous mass* approach is also similar to the Le Bonian (1985/2002) notion of crowds as an unthinking mass who act at a primitive psychological level, where there is no sense of individuality and thus is reminiscent of the broader mass society narrative, where the crowd is treated as an 'undifferentiated whole' (Giner, 1976, p. 47); the mass lacks capacity for moral sense, or a sense of direction. Models in this subtype are not behaviourally realistic because there are no individuals, and therefore there is no room for individual cognition from which meaningful group behaviour can emerge. As mentioned previously, although models in this approach can simulate one crowd where members move together in a limited number of scenarios such as evacuation through one route, this account cannot explain collective behaviour in all situations, such as where there are two or more psychological crowds, or two crowds in contraflow.

In Galea, Owen, and Lawrence's (1996) model, the importance of each member of the crowd having individual attributes which change how people act throughout the simulation is emphasized. Although this was an important development for approaching psychological realism, it was at the cost of modelling collective behaviour. Granularity is obtained at the cost of collectivity. In the mass of individuals approach, there is no collective behaviour because the crowd members act as individuals without any sense of the commonality which is required for collective group behaviour. To create a realistic model of collective behaviour, modellers need to understand how the individual can become part of a psychological crowd. Thus, modellers need to implement the capacity of crowd members to act either as an individual or as a member of the crowd depending upon whether the person categorises themselves as an individual within a physical crowd, or as a member of the psychological crowd.

The crowd as small groups

Unlike the '*mass*' type, models within the '*small groups*' type have various levels of connections between the members of the crowd. The models in this subtype are a significant development in crowd modelling as they recognize and implement the importance of groupness and how this can affect the behaviour of the crowd members. However, the 'small groups' type falls short of realistically modelling large crowd behaviour as it only includes small groups within a crowd. Increasing granularity (small-group level variation within a physical crowd) loses the sense of 'groupness' at the crowd level because the focus is upon numerous small groups within the crowd. The approach therefore does not explain *collective* behaviour where the crowd is one group. By doing this, the models are unable to simulate the behaviour of large psychological crowds where the entire crowd shares one group identity. However, each subtype within the 'small groups' type has its own specific advantages and drawbacks.

In the 'non-perceptual groups' subtype of simulation, groups are treated as physical entities rather than being together due to a psychological bond between the members of the group. The original models in this subtype (e.g., Goldenstein et al., 2001; Thompson & Marchant, 1995) were very important for the development of simulations of crowd behaviour because they introduced groups in to the crowd. However, groups are only incorporated in order to make simulations more realistic by claiming that the groups are families or friends. Group membership has no effect on the behaviour of the group apart from staying together throughout the simulation. Although there are now groups, there is no sense of collective behaviour based on a shared group identity.

Within the ‘perceptual groups’ subtype, modellers represent crowd members as being able to know their own group identity and the group identity of others. Although the ability of the crowd members to perceive group membership and act in accordance with it is in line with SCT (Turner et al., 1987), here groups are treated simply as people that are in the same spatial location. Although group membership is dependent upon group members actively categorising themselves as members of that specific group, group membership is limited and only goes as far as crowd members having roles as either a ‘leader’ or a ‘follower’ as opposed to group membership arising from a sense of common identity. Empirical research on group behaviour suggests that psychological group membership is more versatile than this; when people are in a novel crowd situation they can come together through sharing a group identity and act together in a coordinated way, such as by self-organizing and helping one another (Drury, 2012; Drury et al., 2009a). In addition, group membership does not need to be limited to those people within the same spatial location. The shared group identity can spread to include the entire crowd, where people have a shared social identity with others in the crowd and act in a coordinated way with them even if they are not near to each other, for example football fans in a stadium.

Incorporating cognition for collective behaviour

Models in the subtype that come closest to explicating the underlying components of cognitive group membership, and which is consistent with psychological research, is the ‘cognitive groups’ subtype. Examples of this subtype not only incorporated the perception of group membership, but also went further than the ‘perceptual groups’ subtype by incorporating what is claimed as ‘cognition.’ In this subtype ‘cognition’ is instantiated as the ability of people to perceive their own beliefs and the beliefs of others, and group membership is dependent upon shared beliefs and desired actions. Moreover, in some simulations (e.g., Yuan & Tan, 2007), the agents are able to choose whether to act with a group or to act as an individual.

The incorporation of ‘cognition’ brings this subtype closest to implementing principles of SCT in a crowd simulation. Although not explicitly stated in any of the literature that has been reviewed, it could be argued that models in this subtype actually model something of the cognitive shift from being psychologically an individual to becoming a member of a particular social group and taking on that salient identity, which is crucial for collective behaviour to emerge. However, despite these advantages, this approach does not completely model a psychological crowd as the models are yet to make the leap from small ‘cognitive’ groups to large crowds where the members share the same group identity. For example - although not specifically a model of crowd behaviour - van Rooy (2012) uses an ABM to examine SCT by grouping individuals depending upon their shared opinions. Within this model the individuals could communicate their opinions with others and change group affiliation to be with others who shared the same opinions. By defining groups as those who share common opinions van Rooy’s definition of groups approaches psychological realism by basing group membership on a sense of commonality. While groups are still treated as consisting of small numbers, future work could ascertain whether these principles could be extended to an entire crowd.

Toward a cognitive model of collective behaviour

There are a number of factors that must be addressed in order for modellers to create an accurate simulation of collective behaviour. One component that is fundamental to collective behaviour is the perception of groupness: the ability of an individual to know their own group identity and perceive the group identities of others. An issue here is how to quantify the level of identification that a member feels with their group. Identification with a group is not simply a binary ‘identify’ or ‘do not identify’ scenario; modellers should create agents with the potential for variable levels of group identification which are dependent upon the context that the individual is in. Similarly, the effect of group identity upon behaviour is not necessarily linear. Although an increased level of identification may cause individuals to behave in line with the norms of the group, other variables may act as moderators, such as beliefs about legitimacy of actions and levels of self-efficacy. One example of a model which has effectively employed aspects of SCT to simulate collective crowd behaviour is von Sivers et al. (2014). The study described in this article is a first step toward examining the effect of SCT upon collective crowd behaviour during an emergency, and could be used as a marker for future work simulating collective behaviour.

This has been the first comprehensive and up-to-date review of how computer models have conceptualised groups and crowd behaviour. Despite the importance that models used for crowd management and safety are able to realistically simulate crowd behaviour, until now there has not been a review of how modellers approach collective behaviour, or indeed whether they approach it at all. An earlier review by Sime (1985) found that the idea of ‘mass panic’ was influential in how modellers implemented crowd behaviour in safety planning and the design of public spaces. However, modelling approaches have evolved since Sime’s review. There has been an upsurge in the number of crowd simulations since then, with some articles even referencing Sime in their justification for their new approaches to modelling crowd behaviour (e.g., Feinberg & Johnson, 1995; Kamkarian & Hexmoor, 2013). In addition, a recent review of building evacuation simulations by Aguirre et al. (2011) found that modellers using ABMs placed an emphasis on individuality and mass panic and suggested that evacuation simulations need to include other social scientific factors such as norms, leadership, and group identification and membership.

Though both of these reviews were very important for addressing improvements the needed to be made in the crowd modelling literature, our review has gone further than this. We have comprehensively reviewed a broad scope of crowd modelling scenarios from 1977 to 2014, including simulations of crowd events taken from real life events, simulations of crowds in planning for events, literature looking at techniques for modelling crowd behaviour using simulations, and articles which addressed the techniques used to model crowd behaviour. Moreover, we have examined the theoretical underpinnings of each of these 140 articles to determine what assumptions modellers are making about crowd behaviour. This is the first systematic comparison of the crowd modelling literature with current models of crowd behaviour in social psychology.

By examining what crowd modellers are creating and comparing it to empirical research of collective behaviour, we can see what future models need to change. Although models have been successful in simulating crowds without a group identity, as yet simulations have not aimed to model large psychological crowd behaviour. Modellers are yet to model the transformation of people from identifying as an individual to identifying as a member of the crowd. Without this they cannot model meaningful collective behaviour where the behaviour of a large crowd can be understood in terms of group membership, which is needed to explain scenarios where there is more than one crowd present (such as the football fans mentioned previously). To create a realistic model of crowd behaviour, crowd modellers must look to the extensive empirical research on group and crowd behaviour in social psychology.

We propose that to make more realistic simulations of collective behaviour, which can be applied to a broad range of scenarios, modellers must implement aspects from SCT.

Specifically, these simulations should be based on the aspects of SCT which can explain how members of a large crowd share the same group identity, the transformation from the individual identities to the identities as group members, and the subsequent actions which follow from being part of that group. While this would create more realistic models of collective behaviour for modellers, this interdisciplinary work could also benefit social psychologists. By creating models which incorporate SCT and accurately simulate the behaviour that we have found in empirical search, it could help to develop theories of collective behaviour in social psychology. Only by incorporating these aspects that are based on extensive empirical social psychological research will crowd modellers be able to realistically simulate, monitor, and predict collective behaviour in crowds across a wide range of crowd events.

Chapter 3

Paper 2 - Walking together: Behavioural signatures of psychological crowds

Reference:

Templeton, A. Drury, J., Philippides, A. (in review in Royal Society: Open Science).

Walking together: Behavioural signatures of psychological crowds.

Abstract

Research in crowd psychology has demonstrated key differences between the behaviour of *physical* crowds where members are in the same place at the same time, and the collective behaviour of *psychological* crowds where the entire crowd perceive themselves to be part of the same group through a shared social identity. As yet, no research has investigated the behavioural effects that a shared social identity has on crowd movement at a pedestrian level. To investigate the direction and extent to which social identity influences the movement of crowds, 280 trajectories were tracked as participants walked in one of two conditions: 1) a psychological crowd primed to share a social identity; 2) a naturally occurring physical crowd. Behaviour was compared both within and between the conditions. In comparison to the physical crowd, members of the psychological crowd i) walked slower, ii) walked further, and iii) maintained closer proximity. In addition, pedestrians who had to manoeuvre around the psychological crowd walked further and faster than pedestrians who walked in the naturally physical occurring crowd. We conclude that the behavioural differences between physical and psychological crowds must be taken into account when considering crowd behaviour in event safety management and computer models of crowds.

Introduction

Coordinated crowd movement can be seen in numerous situations: a crowd of football fans celebrating together (Stott et al., 2001), pilgrims undertaking the Hajj in Saudi Arabia (Alnabulsi & Drury, 2014), and people in disasters coming together to support one another (Drury et al., 2009a, 2009b). The complexity of crowd movement has made the underlying causes of crowd behaviour a source of fascination across multiple research disciplines. Crowd psychologists have attempted to look at the relationship between individuals and groups in influencing the perceptions and behaviour of the crowd (e.g. Pandey, Stevenson, Shankar, Hopkins, & Reicher, 2014). Computer modellers have researched the factors influencing pedestrian movement in order to create models which accurately predict movement in a variety of crowd scenarios, from evacuations (Gu, Liu, Shiwakoti, & Yang, 2016; Köster, Hartmann, & Klein, 2011), to pedestrian flow in crowded spaces (Kielar & Borrmann, 2016; Lovreglio, Ronchi, & Nilsson, 2015; Zhao et al., 2016). Biologists have shown that we can gain insight to human crowd movement by looking to the behavioural patterns of social insects, fish and other non-human animals (Couzin, Krause, Franks, & Levin, 2005; Rosenthal, Twomey, Hartnett, Wu, & Couzin, 2015). Additionally, physicists have demonstrated that crowd movement can be understood by comparing behaviour to particle physics and Newtonian forces (Moore et al., 2008; Moussaïd et al., 2010). While these disciplines may use separate paths to understand crowd movement, they share the goal of understanding crowd behaviour by exploring how people in crowds self-organise. Crowd psychology has shown that there are differences between *physical* crowds of co-present members, and the collective behaviour of *psychological* crowds where members act as a group due to their shared social identity. No research, however, has examined the behavioural effects social identities can have at a pedestrian movement level. This paper reports a study in which we examine the movement of crowds in one of two conditions: 1) a *psychological* crowd where the entire crowd is primed to share a social identity; 2) a naturally occurring *physical* crowd comprised of small groups and individuals; and determine the factors underlying self-organising behaviour in crowd movements by drawing on theories from social psychology.

Self-organisation in crowds

The way in which crowds self-organise has been researched in four broad areas. First, the effect of socially transferred information on crowd movement has been examined in diverse disciplines. For example, research on birds, marine insects and fish has suggested that collective movement is influenced by non-verbal cues of velocity and the direction of movement of others (Ward, Sumpter, Couzin, Hart, & Krause, 2008), and knowledge of group structures based on cues from individuals (Couzin, Krause, James, Ruxton, & Franks, 2002). Visual perception in human crowds has also been suggested to affect movement based on cues on where others in the crowd look (Gallup, Chong, & Couzin, 2012; Gallup et al., 2011) and walk (Boos, Pritz, Lange, & Belz, 2014). A second focus has been the role of leadership and how crowds reach consensus decisions. For example, researchers have investigated how information is disseminated and how effectively crowds reach a target depending on which members of the crowd were informed (Acemonglu, Ozdaglar, & ParandehGheibi, 2010; Conradt & Roper, 2005; Dyer, Johansson, Helbing, Couzin, & Krause, 2009; Faria, Dyer, Tosh, & Krause, 2010; Moussaïd, Garnier, Theraulaz, & Helbing, 2009; Sumpter, 2006). Third, the influence of both macroscopic and microscopic level features of crowd behaviour on coordinated movement of the crowd have been analysed. Macroscopic computer models have examined the influence of factors such as density on pedestrian movement in emergency situations (Fang et al., 2003; Johansson et al., 2012; Lee & Hughes, 2006). Conversely, microscopic modelling has examined the effect of an individual's movements on physical crowds, such as a pedestrian's motivation to avoid collisions (Degond et al., 2013; Moussaïd et al., 2009) and their stepping behaviour (Seitz, Dietrich, & Köster, 2014, 2015).

An important growing fourth area of research is examining the effect of group behaviour on crowd movement. For instance, Moussaïd et al. (2010) looked at the formations of approximately 1,500 pedestrian groups in natural conditions to analyse their walking patterns and how groups influenced crowd flow, finding that small groups form ‘V’ formations as they move through the crowd. Research by Vizzari et al. (2015) explored the role of groups on crowd flow by manipulating the size of group to be either a single pedestrian, three pairs of pedestrians, two groups of three pedestrians, or two groups of six pedestrians. This unique experiment told the pedestrians in the group conditions to stay together as friends or relatives would, and found that when the groups tried to maintain a formation it increased their travel time. The effect of groups in crowds have also been applied to affiliation behaviour in evacuations (Sime, 1983), egress (Bode, Holl, Mehner, & Seyfried, 2015; Braun, Musse, Oliveira, & Bodmann, 2003; Yang, Zhao, Li, & Fang, 2005) and the walking formations of groups in crowds (Köster, Treml, Seitz, & Klein, 2014; Reuter et al., 2014).

Crucially, however, these studies investigate subgroups within a crowd rather than when an entire crowd acts as a group nor, with the exception of Vizzari et al. (2015), do they analyse what makes a ‘group’. Indeed, very few studies on the self-organisation of crowds have examined the psychological underpinnings of what a ‘crowd’ is and how this could influence movement. Such an understanding is needed to explain why one type of crowd exhibits greater, or different, self-organising collective behaviour compared to another. One social psychological approach that has shown that there are key differences between crowds who share a social identity and those who do not, and can elucidate whether and how social psychological factors may influence crowd self-organisation, is SCT (Turner et al., 1987).

Defining the 'crowd'

Understanding the psychology of a crowd can help explain important behavioural differences between, for example, a crowd of commuters walking during rush hour and a crowd of sightseeing tourists who coordinate their behaviour to remain together. Reicher (2011) distinguishes between *physical* crowds, which are comprised of individuals who are physically co-present but do not share a sense of being in the same group (such as the commuters), and *psychological* crowds where members also share a sense of 'group-ness' (such as the sightseeing tourists who see themselves as a group). SCT can explain this distinction and demonstrates that physical aggregates of individuals can become a psychological group through the process of depersonalisation: individuals self-stereotype themselves as being in a group, so they shift from their personal identity to identifying as a member of a group (Turner et al. 1987). It is through this shared social identity that collective behaviour becomes possible (Turner, 1985).

SCT has been applied to a multitude of crowd scenarios to show how social identity can explain features of psychological crowds, such as feelings of safety during the Hajj (Alnabulsi & Drury, 2014), people coordinating their actions in emergency evacuations (Drury et al., 2009a, 2009b; Drury et al., 2015), and intimacy behaviours (Neville & Reicher, 2011). However, only a limited number of studies have examined the behavioural consequences of shared social identity in a crowd, and none have applied the principles to modelling pedestrian behaviour. Indeed, one of the key behavioural predictions of SCT - that ingroup members will remain together based on their shared social identities - is yet to be quantified in large crowd behaviour.

Experimental research has examined the extent to which social identity can affect behaviour such as the maintenance of physical distance (or proximity) between small groups of people. Research by Novelli et al. (2010) found that when participants defined themselves as being in the same group as another person in the room, the participants moved their chairs significantly closer together than if the other person was perceived to be a member of a different group. Crucially, Drury et al. (2009a) found that survivors of the 2005 London bombings became a psychological crowd in the aftermath of the bombs and remained together to help one another. We suggest that these findings can be used to derive predictions about the effect of social identity on proximity behaviours in walking crowds: specifically, those who are in the same group are willing to be closer to one another and will therefore try to stay together, which will have consequences for flow rates.

Given the findings from social psychology that people with a shared social identity coordinate their behaviour and are willing to be physically closer to ingroup members, our research investigates the effect of social identity on the movement of psychological crowds compared to physical crowds. We argue that due to ingroup members attempting to remain together, there are distinct behavioural signatures which distinguish psychological crowds from physical crowds, and that these are explicable in terms of shared social identity. Using minimal group manipulation techniques from social psychology (Haslam, 2004), we compare the walking behaviour of a psychological crowd and a physical crowd to assess the effect a shared social identity has on walking behaviour. In particular, we analyse differences in walking speed, distance walked, and proximity between the crowd members. We hypothesise that shared social identity will cause members of the psychological crowd to 1) alter their speed to remain with other psychological crowd members, 2) alter the distance walked to remain together, and 3) stay together by 3a) maintaining closer proximity and 3b) walking in larger subgroups than in the physical crowds.

Methodology

Design and materials

A field study of walking behaviour in two crowds was conducted at the University of Sussex campus in England. In the experimental condition, a *psychological* crowd was created by priming participants to share a social identity. These participants (N = 120) signed up to be part of a study on walking behaviour and were selected based on their attendance of a second year Psychology lecture. A shared social identity amongst participants was evoked using standard forms of social identity manipulation (Haslam, 2004): we provided every participant in the psychological crowd with an identity prime of a black baseball cap with a 'Sussex Psychology' logo on it. This logo was emblematic of a social identity already available to each participant and was used to make that social identity salient. It also enabled participants to see who else was in their group and allowed the experimenters to track who had been primed to share a social identity. Each participant was asked to walk from the lecture to a nearby location on campus. Around these recruited participants were an additional 47 pedestrians walking in the same area.

One week prior to the experimental conditions, we filmed a control condition consisting of 121 participants who were primarily comprised of the same second year Psychology students at Sussex as they left their lecture to walk to the other side of campus. This was a naturally occurring *physical* crowd, as the participants were not manipulated. We ensured that the person filming was visible by wearing high visibility jacket and filming from a low bridge directly above the path the crowd walked under. We attempted to keep the conditions as similar as possible within the limits of fieldwork. Both crowds were filmed at the same time of day a fortnight apart in the same weather conditions (sunny) after their lecture to ensure they had the same timetable commitments. Importantly, participants in both the psychological and physical crowd conditions were largely comprised of the same people to ensure that any pre-existing relationships between the crowd members were the same before priming the crowd to share a social identity, thus keeping any friendship groups consistent in both conditions.

Filming was performed with a Nikon PixPro AZ361 digital camera with a 36x wide 24-864mm equivalent Aspheric HD Zoom Lens with no zoom or lens distortion. We filmed the participants from above to aid participant tracking as they walked along a section of the path on the route (length = 10 metres, width = 3.75 metres), with the camera set up at the centre of a low bridge crossing the path perpendicularly. We selected this path as it is an area where students walk between lectures and the main campus, and by keeping conditions as similar as possible, hoped that the participants would be met with similar counterflow pedestrians around both crowds. There were 55 people in counterflow to the physical crowd, and 34 people in counterflow to the psychological crowd. Additionally, there were 13 people walking the same direction as the psychological crowd in that condition, but on the other side of the path to those walking in counterflow.

To enable between-groups analysis, those in the footage were classified as follows: participants primed to share a social identity were classified as Group 1 (n = 112); the people who were not recruited and were walking in the same direction as the psychological crowd (towards the camera) were classified as Group 2 (n = 13), and those who were walking in counterflow to the crowd (away from the camera) were classified as Group 3 (n = 34). Within the physical crowd condition, those walking towards the camera were classified as Group 4 (n = 66), and those walking away from the camera were classified as Group 5 (n = 55). Please see Figure 4 for snapshots of the groups in the footage, where picture (a) depicts the groups in the experimental condition, and picture (b) depicts the groups in the control condition.

(a) (b)

Figure 4. Snapshots of the pedestrians in both crowd conditions.

Trajectory analysis

The positions of the crowd members were extracted using custom-made MATLAB software which allowed manual selection of each participant every 5 frames (frame rate 24 frames per second), to reconstruct their trajectories as they walked throughout the footage. Head positions were tracked because the pedestrians' positions on the ground could not be derived from the pedestrians' feet positions, as these were not always visible due to the density of the crowd and angle of filming. The data was transformed from the camera angle above the bridge to a directly top-down planar view in order to assess the locations of the pedestrians on the ground, defined to be approximately the centre-of-mass of their bodies. The transformation matrix was derived by selecting corners of a 3.75 metres by 5 metres rectangle painted on the ground.

To perform the transformation to a planar view, we assumed a constant height for the participants of 169 cm (which is the middle height between the average heights of UK men and women) and that their heads were directly above their centre-of-mass. This process will lead to errors from swaying of heads and height differences. To quantify the extent of these errors, we used a sample of participants whose feet were visible, and compared the planar positions derived from their feet positions (the average position between their feet) to the planar positions derived from head positions. While there are some large differences, the median and interquartile ranges for the differences are 18 +/- 13 cm for the physical crowd, and 28 +/- 17 cm for the psychological crowd. Importantly, the differences within participants' trajectories are consistent, suggesting that the differences are predominantly caused by height variation between participants. This is reinforced by the fact that errors are greater in the y-axis which is perpendicular to the camera plane and decrease as the participants come towards the camera. Since the errors are approximately consistent within each trajectory, they do not affect measures of speed and distance travelled.

The pedestrians' projected feet positions were then used to ascertain their walking speed, distance walked, and the proximity between individuals. Speed for each pedestrian was calculated as distance/time, where time = 0.2085 = 1 second divided by frame rate multiplied by 5 (as 5 is the frame gap used when tracking trajectories). The distance each pedestrian walked was calculated by summing the distance between the coordinates of each step. The space around each pedestrian was measured using Voronoi tessellation areas which sets a polygon around each member of the crowd based on the distance to their nearest neighbours at each time point. These areas were calculated using Sievers's (2012) method for Voronoi decomposition and implemented in MATLAB, with vertices constrained so that the maximum tessellation area radius is 1 metre to avoid artificially inflating the space around individuals walking alone or on the periphery of the crowd.

To ascertain how much space individuals maintained around them, the footage of both crowds was sliced into time points to get snapshots of the pedestrian locations every 4.17 seconds (100 frames), producing 10 time points for each condition and spanning the entirety of the psychological crowd footage. One possible issue is that there were different numbers of people at different time points in the experimental condition compared to the control condition, and the number of people around the psychological crowd changes as they walk through the footage. As such, Latent Growth Curve Analysis was used in R to determine 1) whether there were differences in tessellation areas between groups, 2) whether their tessellation areas changed over time, and 3) whether this was affected by the number of people in the area.

Following this, a prima facie analysis was conducted to determine how pedestrian groups maintained formation while walking. Hierarchical agglomerative cluster analysis was used with between-groups linkage, Euclidian distance and standardised z-scores, to group participants based on the distance between their locations at the different time points. This explored whether the crowds split into smaller groups through classifying sub-groups (or clusters) by examining the optimum number of clusters within each time point. We then also compared which participants were in clusters in successive time points to ascertain whether clusters remained together.

Results

Speed of movement

Kolmogorov-Smirnov tests revealed that Groups 1, 2, 3, and 5 did not significantly deviate from normal distribution, but Group 4 was non-normally distributed (see Table 2 for *D*-values, degrees of freedom, and *p*-values, and Figure 5 for means and standard errors). Independent t-tests were used to compare groups that were parametric, and Kruskal-Wallis tests were used to compare groups where one or both groups were non-parametric.

Table 2

Kolmogorov-Smirnov tests for each group for speed of movement, distance walked, and tessellation areas. Non-normal distributions are indicated in bold

	Speed			Distance			Tessellation areas		
	D	df	*p*	*D*	df	p	*D*	df	*p*
Group 1	.06	112	.200	.10	112	**.014**	.10	418	**.001**
Group 2	.15	13	.200	.29	13	**.005**	.12	25	.200
Group 3	.11	34	.200	.34	34	**.001**	.07	56	.200
Group 4	.15	66	**.001**	.07	66	.200	.07	47	.200
Group 5	.08	55	.200	.08	55	.200	.10	52	.200

When comparing the groups within conditions, on average, Group 1 walked significantly slower than those in Group 2 (walking in the same direction as Group 1), -45.17, BCa 95% CI [-58.93, -31.41], $t(12.15) = -7.13$, $p < .001$, $r = .899$. Group 1 also walked significantly slower than those in Group 3 (in counterflow to Group 1), -26.82, BCa 95% CI [-34.41, -19.24], $t(34.17) = -7.18$, $p < .001$, $r = .776$. On average, Group 2 walked faster than Group 3, -18.35, BCa 95% CI [3.97, 32.73], $t(45) = 2.57$, $p = .014$, $r = .358$. In the control condition, Group 4 (*Mean rank* = 66.88) walked significantly faster than Group 5 (those walking in counterflow to Group 4, *Mean rank* = 53.95), $H(1) = 5.19$, $p = .023$.

When comparing the group across crowd conditions, crucially, on average participants walked significantly more slowly when they were primed to share social identity (Group 1 *Mean rank* = 58.30), than when they were not (Group 4 *Mean rank* = 142.44), $H(1) = 110.72$, $p < .001$. An independent t-test found that Group 1 also moved significantly slower than those in counterflow in the control condition, Group 5 -16.389, BCa 95% CI [-19.78, 13.00], $t(64.08) = -9.66$, $p < .001$, $r = .770$. Those going around the psychological crowd (Group 2 *Mean rank* = 59.54) walked faster than those going the same direction in the control crowd (Group 4 *Mean rank* = 36.15), $H(1) = 11.28$, $p < .001$, suggesting that the psychological crowd has an effect on people walking in the same area due to manoeuvring around it. This is also found when comparing those in counterflow to the psychological crowd (Group 3) who walked significantly faster than and those walking the same direction in the control condition (Group 5) -10.44, BCa 95% CI [2.30, 18.57], $t(45.89) = 2.58$, $p = .013$, $r = .356$. Overall, these results confirm Hypothesis 1.

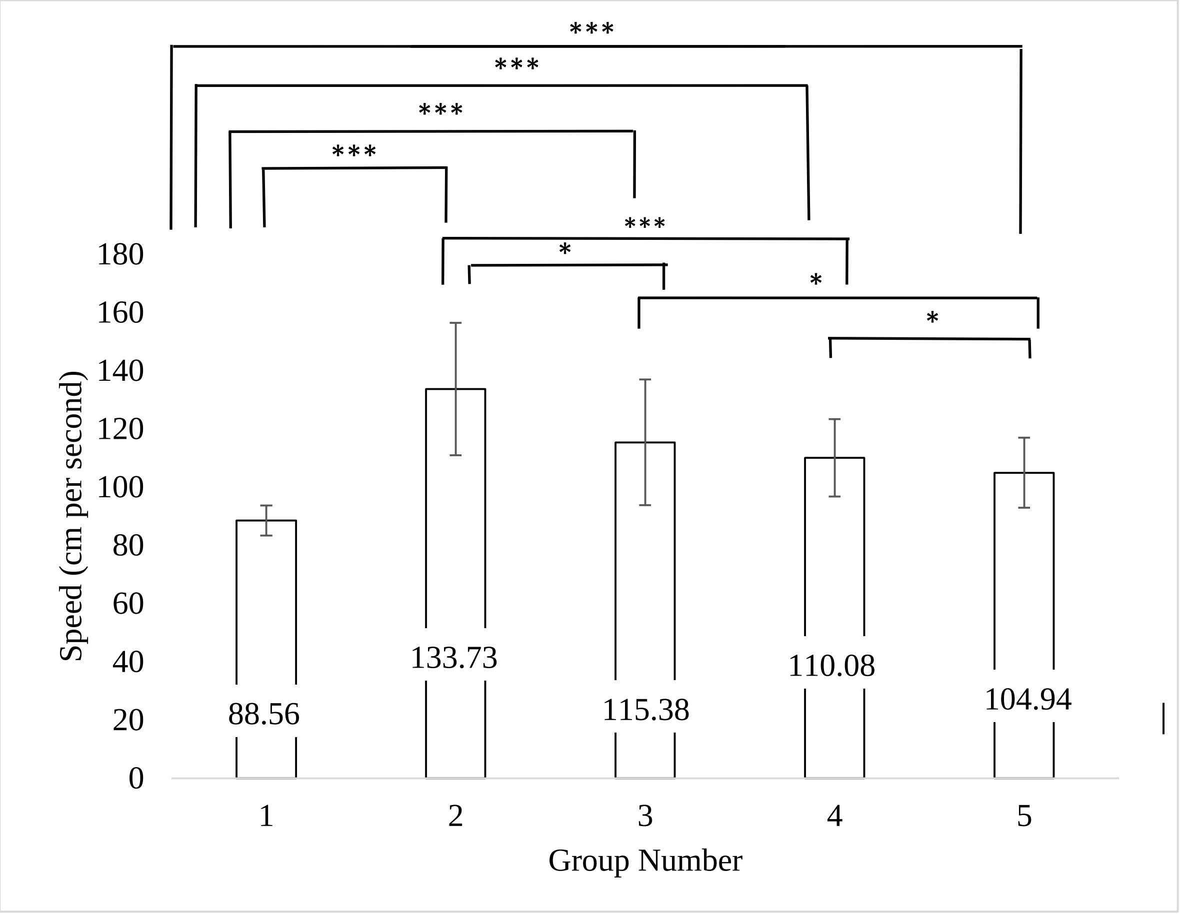

Figure 5: Means and standard errors for the speed each group walked, * indicates $p < .05$, *** indicates p < .001. *SE* for groups: 1 = 0.49; 2 = 6.30; 3 = 3.70; 4 = 1.63; 5 = 1.63.

Distance

Kolmogorov-Smirnov tests revealed the distance of Groups 1, 2, and 3 were non-normally distributed, but Groups 4 and 5 did not deviate significantly from normal (see Table 2 for D-values, degrees of freedom, and p-values, see Figure 6 for means and standard errors). Again, independent t-tests were used to compare groups that were parametric, and Kruskal-Wallis tests were used to compare groups where one or both groups were non-parametric.

Between-groups analysis for groups within conditions showed that participants in Group 1 (*Mean rank* = 68.49) walked significantly further when compared to Group 2 (*Mean rank* = 15.69), $H(1) = 24.73$, $p < .001$, and when Group 1 (*Mean rank* = 83.08) was compared to Group 3 (*Mean rank* = 41.94), $H(1) = 24.68$, $p < .001$. Group 3 (*Mean rank* = 28.88) also walked significantly further than Group 2 (*Mean rank* = 11.23), $H(1) = 15.59$, $p < .001$, possibly due to Group 3 being in counterflow with Group 1 and 2 so having to manoeuvre around them. In the control condition, Group 4 walked significantly further than Group 5, -6.02, BCa 95% CI [-10.83, - 1.22], $t(119) = -2.48$, $p = .014$, $r = .05$.

Comparisons across crowd conditions found that Group 1 (*Mean rank* = 122) walked significantly further than Group 4 (*Mean rank* = 35.50), $H(1) = 123.48$, $p < .001$, supporting Hypothesis 2 that those who share a social identity walked further in order to remain together. Group 1 (*Mean rank* = 111.50) also walked faster than Group 5 (*Mean rank* = 28), $H(1) = 110.01$, $p < .001$. Group 2 (*Mean rank* = 73) walked significantly further than Group 4 (*Mean rank* = 33.50), $H(1) = 32.18$, $p < .001$. Group 3 (*Mean rank* = 72.50) also walked significantly further than its counterpart in the control condition, Group 5 (*Mean rank* = 28), $H(1) = 62.33$, $p < .001$, again suggesting that the psychological crowd affected those around it.

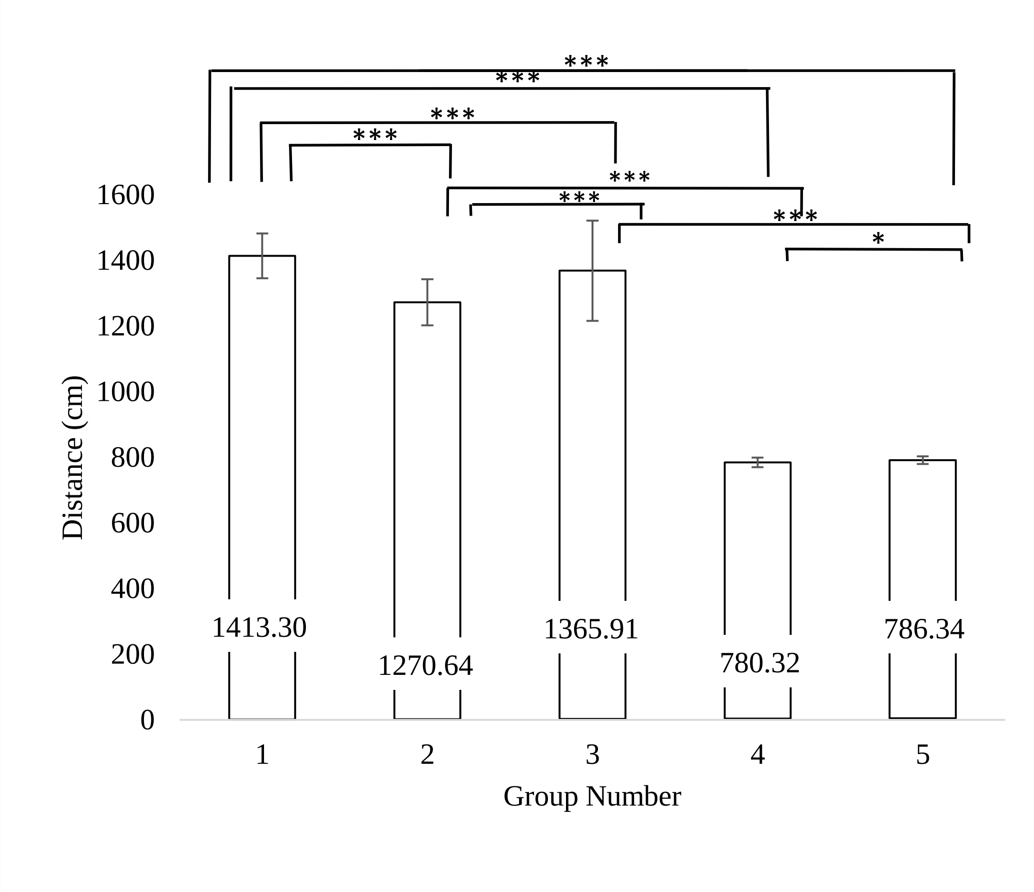

Figure 6: Means and standard errors for the distance each group walked, * indicates $p < .05$, *** indicates p < .001. *SE* for groups: 1 = 6.47; 2 = 19.52; 3 = 26.20; 4 = 1.19; 5 = 1.56.

Proximity

Distance measures

Kolmogorov-Smirnov tests indicated the mean tessellation areas of Group 1 were non-normally distributed, but all others groups did not deviate significantly from normal (see Table 2 for *D*-values, degrees of freedom, and *p*-values). The mean tessellation areas for each group across all time points were, Group 1: M = 10383.29, SD = 5503.68; Group 2: M = 20218.67, SD = 5626.12; Group 3: M = 17732.70, SD = 6493.58; Group 4: M = 20506.39, SD = 6404.64, Group 5: M = 18298.48, SD = 7006.30. Please see Figure 7 for group medians and standard deviations, where red lines indicate the medians, boxes cover the 25th and 75th percentile and whiskers extend to 1.5 times the inter-quartile range, and red +'s indicate outliers.

Between-groups analysis was conducted on the mean tessellation areas across all time points. The tessellation areas of people in Group 1 were significantly smaller than those for people in all other groups, supporting our Hypothesis 3a. Group 1 (*Mean rank* = 212.23) has significantly smaller tessellation areas than Group 2 (*Mean rank* = 385.32), $H(1) = 43.11$, $p < .001$; and Group 3 (Group 1 *Mean rank* = 220.10, Group 3 *Mean rank* = 367.38), $H(1) = 57.10$, $p < .001$; and Group 4 (Group 1 *Mean rank* = 214.95, Group 4 *Mean rank* = 393.54), $H(1) = 74.63$, $p < .001$; and Group 5 (Group 1 *Mean rank* = 218.65, Group 5 *Mean rank* = 370.94), $H(1) = 58.14$, $p < .001$, showing that those in the psychological crowd maintained less space around them. A one-way ANoVA demonstrated that all other between-groups comparisons were non-significant suggesting there was no effect of group on tessellation size, $F(3, 176) = 2.13$, $p = .099$, $w = .135$. The linear trend was non-significant, $F(1, 176) = .38$, $p = .536$, $w = .171$, indicating no proportional change with group number.

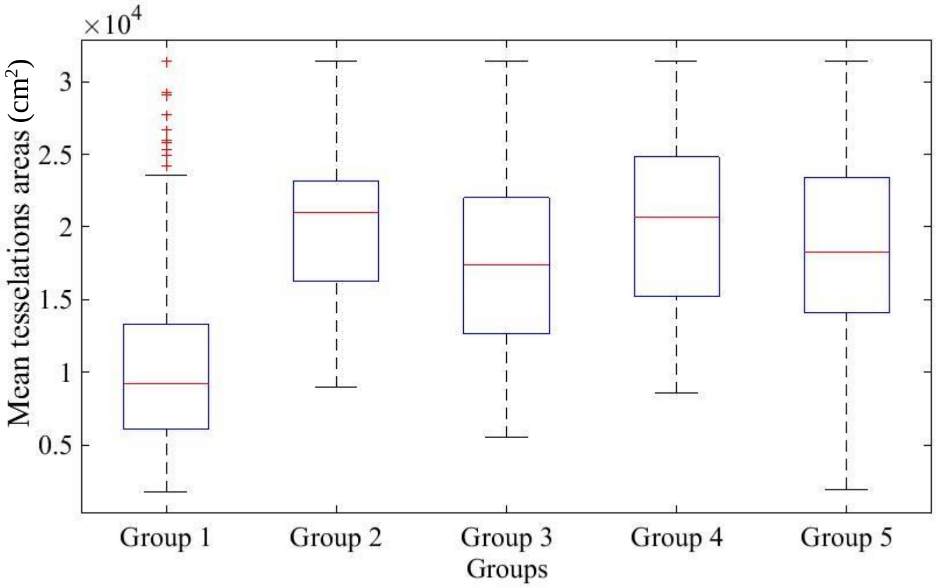

Figure 7: The distribution of tessellation areas for the different groups gathered over 10 time points.

Latent Growth Curve modelling was used to predict 1) the effect of group on tessellation areas, 2) the effect of group on changes in tessellation areas over three time points, and 3) the effect of number of people on the tessellation areas. We used the tessellation areas of participants from when their first tessellation area was calculated (Time 1), and their tessellation areas at the following two time points (Time 2 and Time 3). The intercept was weighted as 1 on each time point to constrain them as equal. The slope was weighted on the time points as Time 1_0, Time 2_1, and Time 3_2 as the times were equally spaced at 4.17 seconds apart. The intercept and slopes were extracted across Time 1, Time 2, and Time 3 and used as estimates of (a) baseline tessellation areas and (b) increase or decline in tessellation areas across the successive time points. We allowed a direct relationship between the number of people in the area at each time point and the corresponding tessellation areas of the participants at those time points. Group was regressed on to the intercept and slope, and participants were coded in their relevant groups. Robust maximum likelihood and full information maximum-likelihood (FIML) were used for missing data in Time 3 as the faster speed of pedestrians in Groups 4 and 5 meant that some participants could only be tracked across two time points.

We used the criteria suggested by Hu and Bentler (1999) to assess model fit, which suggests RMSEA < .06, SRMR < .08, CFI > .95. This led us to consider our model provided adequate fit, RMSEA = .07, SRMR = .08, CFI = .98. Notably, chi-squared was non-significant, $\chi^2(7) = 11.60$, $p = .114$. In the model, the number of people was a non-significant predictor on tessellation areas at Time 1, $\beta = .090$, $p = .167$, and Time 2, $\beta = .011$, $p = .167$, but was a significant predictor at Time 3, $\beta = .128$, $p = .024$, which had the highest number of people. The groups have significantly different initial tessellation areas at Time 1, $\beta = .347$, $p < .001$, with people in Groups 2, 3, 4, and 5 appearing to have larger initial tessellation areas. Group was a significant predictor of change over time, $\beta = .244$, $p = .029$, indicating that the change of tessellation areas over time were different for the groups when including the number of people in the area (see Figure 8 for path diagram and R^2 values). As can be seen in Figure 9, as the number of people increases the tessellation areas were affected in Groups 2, 3, 4, and 5, but the tessellation areas for Group 1 remained mostly constant regardless of the number of people in the area. This indicates support for our Hypothesis 3a that those who shared a social identity remained in closer proximity even when there was space available to spread out.

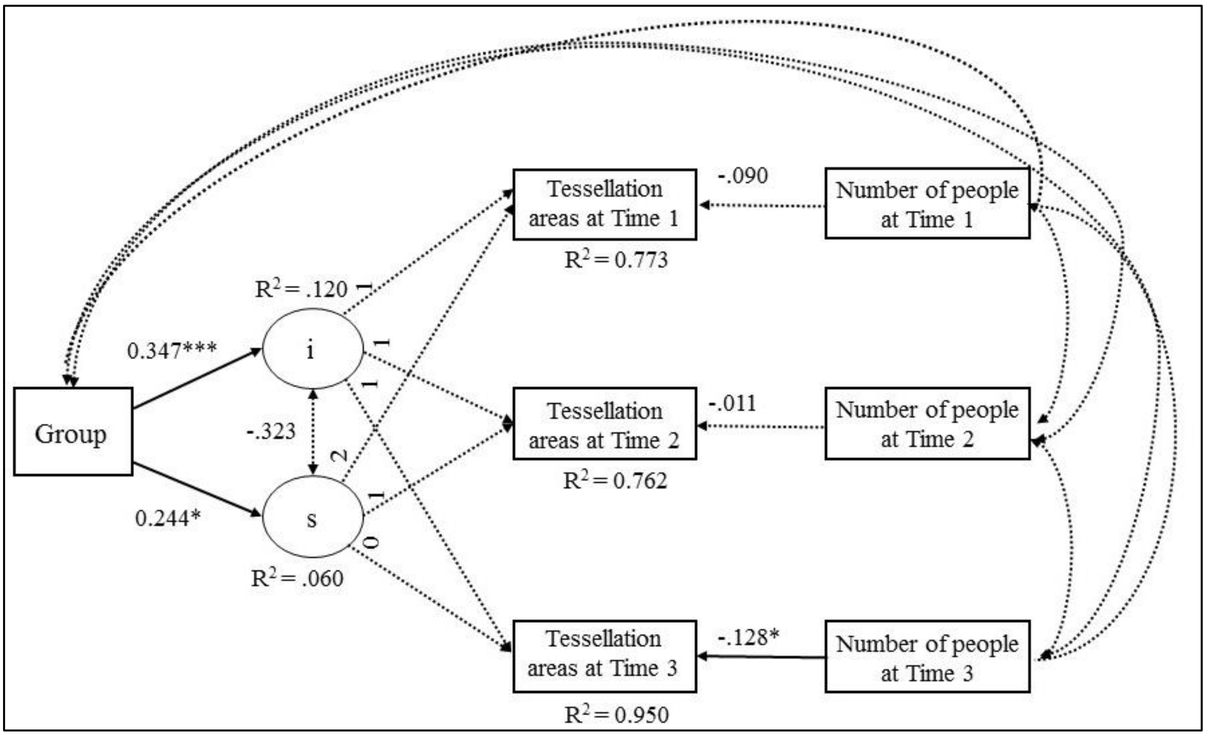

Figure 8: Path model where standardised estimates indicate tessellation areas as a function of group and number of people in the area. Solid lines indicate significant pathways, and dotted lines indicate non-significant pathways (*$p < .05$, **$p < .01$, ***$p < .001$).

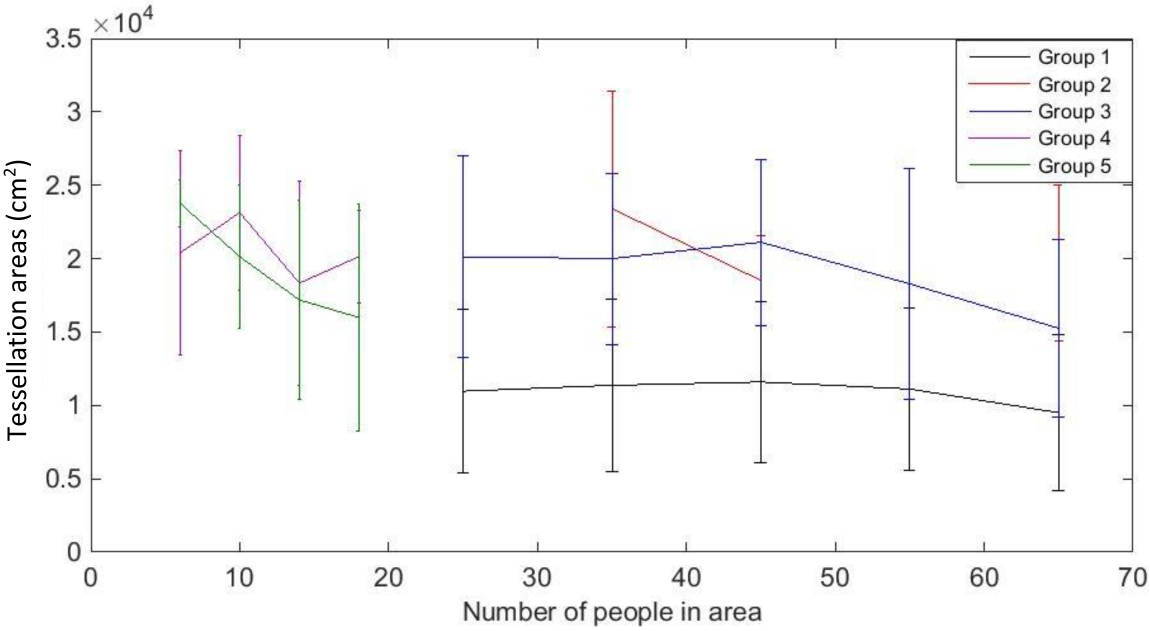

Figure 9: The median tessellation areas of each group as the number of pedestrians increase. Error bars indicate the 25th and 75th percentiles of the data.

Subgroup size

Cluster analysis compared the number of subgroups within each group and found that those with a shared social identity (Group 1) walked in larger subgroups. The largest clusters in Groups 4 and 5 comprised three people, compared to clusters of 11 in Group 1. Moreover, the subgroups typically remained together while walking along the path throughout the progression of the time points, supporting our Hypothesis 3b that the psychological crowd would remain together in larger groups than in the physical crowd when they were not primed to share a social identity. This provides prima facie support for our Hypothesis 3b that larger subgroups occur and are maintained in the psychological crowd, rather than splitting into the smaller groups that can be seen in physical crowds. For a snapshot of the clusters, see Figure 10 where green diamonds denote pedestrians whose trajectories across the entire footage have been demonstrated. The progression of one group is shown in the psychological crowd, but two groups are shown in the physical crowd due to the faster walking pace of the pedestrians meaning they could not be tracked across all three time points (note that there are two groups shown in time point 8 of the physical crowd).

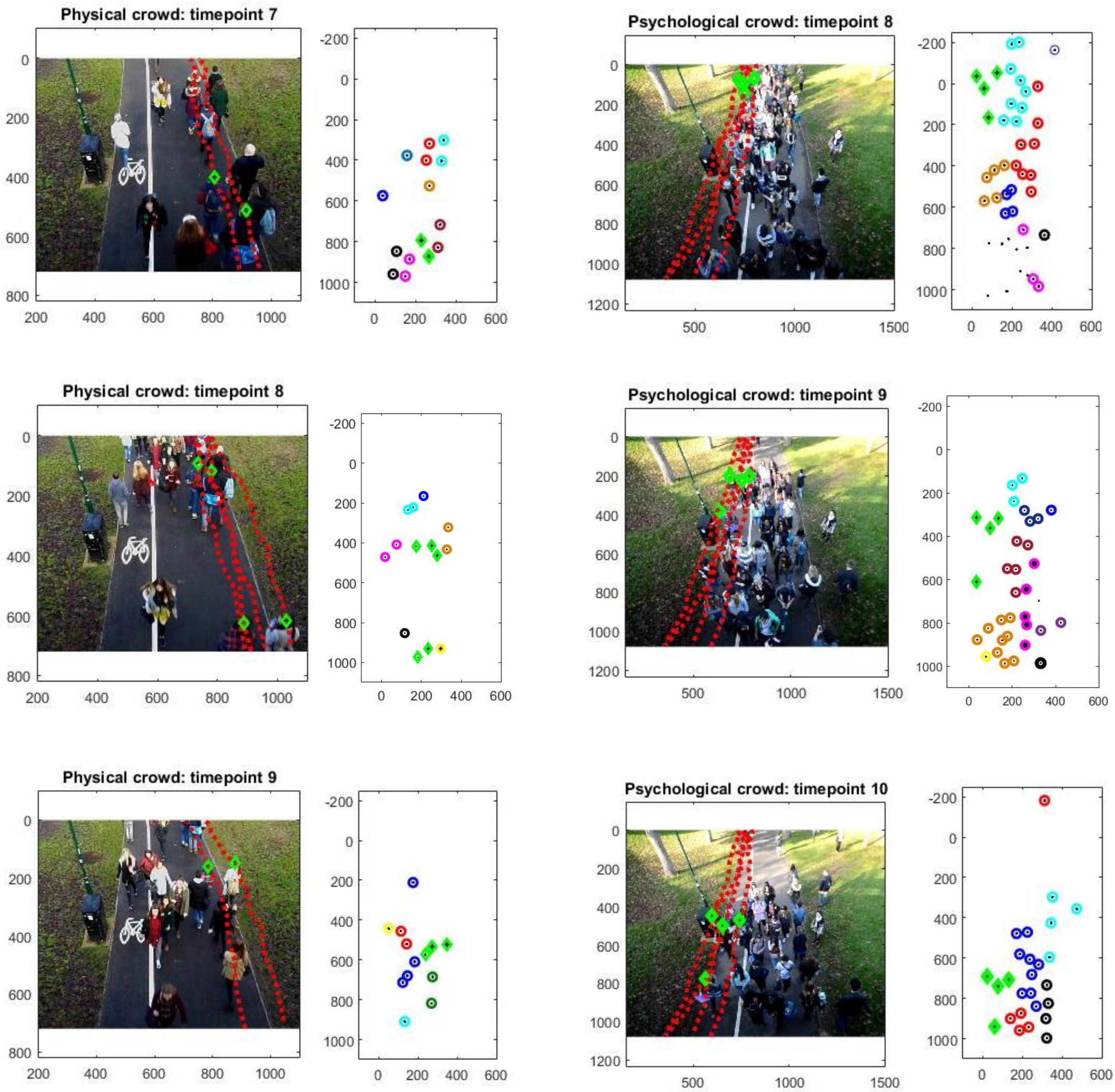

Figure 10: The progression of groups identified by cluster analysis over three time points in the physical and psychological crowds.

Discussion

By priming a crowd to share a social identity and comparing their behaviour to a naturally occurring crowd, we show core behavioural differences between psychological and physical crowds. We demonstrate that a shared sense of social identity motivated more coordinated behaviour amongst the participants. First, the psychological crowd walked slower than the other groups. Second, they walked further than the other groups. Third, they maintained closer proximity regardless of the number of people in the area. Fourth, they consisted of larger groups within the crowd and did not split into the small clusters seen in physical crowd.

Further, those who had to manoeuvre around the psychological crowd walked faster and walked further than when no psychological crowd was present (even when in counterflow), while people walking the same direction as the psychological crowd maintained more distance around themselves than people in the physical crowd condition. This is additional but complementary to our hypotheses, and suggests that when a large psychological crowd was present, those outside it change their behaviour in order to avoid walking through the crowd.

These behavioural patterns have implications for understanding the self-organising behaviour of psychological crowds. Research in social psychology has shown that numerous crowds with shared social identities exhibit self-organising behaviour and would be considered a psychological crowd as defined in this study. For example, at the Hajj when pilgrims coordinate their behaviour to perform rituals in potentially dangerous densities (Alnabulsi & Drury, 2014), or when a physical crowd become a psychological crowd in an emergency and form orderly lines to evacuate and let others go first and stay back to help people who are injured (Drury et al., 2009a). Here we provide quantified behavioural signatures of the movements of both psychological and physical crowds, showing how a shared social identity leads to different behaviours.

To our knowledge, there is no group-specific norm among Sussex Psychology students of walking in close proximity. As such, our findings can be extrapolated to other psychological crowds and have particular relevance to research on the effect of information transference and leadership in crowd behaviour, as we demonstrate that social identity has an effect on self-organising behaviour in psychological crowds. In contrast to previous literature (such as Acemonglu et al., 2010; Dyer et al., 2009; Moussaïd et al., 2009) in our study we provided no leader or information other than the location they were directed to, which group the members were in, and who else was in their group (indicated by the identity markers on their hats). Having identity markers as a source of information for crowd members might be thought to be artificial, but it is seen in other crowd events, such as sporting events where fans wear team memorabilia, or music events where attendees wear band emblems. We showed that shared social identity was the key information held by participants and the cause of the coordinated behaviour. While research on leadership and transference of information may be applied to physical crowds, our results suggest that leadership is not necessary for self-organised coordination in psychological crowds.

People walking in counterflow to the psychological crowd, rather than attempting to walk through the psychological crowd, steered to the side of the crowd and walked in counterflow between the psychological crowd and those who were walking in the same direction as the psychological crowd. This could indicate that they treated the psychological crowd as one group and could distinguish between the psychological crowd and those in Group 2 who were walking in the same direction. Similarly, rather than joining the psychological crowd, Group 2 avoided the crowd and moved around it, indicating that they too perceived the crowd as an entity due to the coordinated behaviour. We thus suggest that a psychological crowd may cause people around the crowd to walk differently than when a merely physical crowd is present. However, one limitation of the present study is that these avoidance behaviours could be due to the lack of available room to walk in (due to the higher density of Group 1 than all other groups) rather than perception of the psychological group as a whole. Future research should examine whether the psychological crowd was perceived as an entity by outsiders, and whether the same behaviour occurs when there is more space available for the pedestrians to avoid the crowd.

In previous research, social identity has been shown to affect how a crowd interacts in emergency evacuations, such as survivors stopping to stay with and help others in their group, therefore delaying evacuation time (Drury et al., 2009a; Reuter et al., 2012). Our results indicate that the crowd members may cluster together even when there is space available. The decreased walking speed of the psychological crowd supports the findings of Vizzari et al. (2015) that the speed of groups is reduced when they attempt to keep formation. This is an important consideration for safety planning of crowd events and crowd models that assume crowds will split up into smaller subgroups (Braun et al., 2003). Our results suggest that when a shared social identity is salient, the members of the crowd may remain in larger groups rather than splitting up or acting as individuals, as we observed in the physical crowd. Future research could extend this principle to crowd safety to explore the effect of social identity on cluster sizes within crowds, and how large clusters remaining together effects ingress and egress time.

As Reuter et al. (2014) indicate, computer models are increasingly being used to plan for crowd behaviour in public spaces, and to do this safely they must be validated using real-world data. However, a recent systematic review of crowd simulations (Templeton, Drury, & Philippides, 2015) and found that, as yet, modellers have not incorporated the different behaviour of psychological crowds where an entire crowd shares a social identity. Here we quantify how social identity influences the behaviour of people in psychological crowds indicating that it should be considered in interpretations of self-organising crowd behaviour. The differences in speed, distance and proximity are crucial factors to consider when planning how a crowd will behave during ingress, egress, or in the event of an emergency situation. Crowd safety professionals and crowd modellers should thus develop crowd planning and simulations that distinguish the behavioural signatures of psychological and physical crowds in order to accurately replicate these different behavioural patterns.

Chapter 4

Paper 3 - Placing intragroup and intergroup relations into pedestrian flow dynamics

Reference:

Templeton, A., Drury, J., & Philippides, A. (Submitted to Royal Society: Open Science).

Placing intragroup and intergroup relations into pedestrian flow dynamics.

Abstract

Understanding pedestrian flow is important to predict crowd behaviour at mass events, but research in crowd dynamics has often treated crowds as either a mass of individuals acting independently or merely involving small groups. Little research has examined how large groups interact in a shared space, for example at sporting events, festivals, and transport hubs. Previous research in social psychology has demonstrated that social identities can influence the micro-level movement of psychological groups, yet thus far, no research has investigated the behavioural effects social identities can have when two large psychological groups are co-present. The present study investigates the effect that the presence of large groups with different social identities can have on pedestrian behaviour, focussing on how groups with different social identities walk in counterflow. Participants (N = 54) were split into two groups and primed to have identities as either ‘team A’ or ‘team B’. Prior to walking, questionnaires measured identification towards ingroup and outgroup members. The trajectories of all pedestrians were tracked to measure their i) speed of movement and distance walked, and ii) proximity between participants when a) team A were the only group present, and b) team A and team B walked in counterflow. Results indicate that, in comparison to walking alone, the presence of another group caused team A to collectively self-organise to reduce their speed and distance walked in order to remain closer to ingroup members. We discuss the significance of intragroup and intergroup dynamics on ingress and egress in computer models of pedestrian flow.

Introduction

Predicting and monitoring pedestrian behaviour is crucial for safety at mass events. Crowd models are commonly used to predict behaviour at sporting events such as at the Olympic Games (Owen, 2012); the religious pilgrimage of the Hajj (Crowdvision, 2017); and to plan for pedestrian behaviour in transport hubs both in ordinary scenarios and emergency evacuations (Burrows, 2015). Crowd models are based on key assumptions about what motivates pedestrian behaviour, but the factors underlying collective behaviour are widely debated. One approach suggests that crowd members merely act as they would as individuals according to their personality (e.g. Bode et al., 2015; Moussaïd & Trauernicht, 2016). Other research proposes that crowd members are guided by visual cues in the environment, such as the distance of the pedestrian to obstacles and other pedestrians (Moussaïd et al., 2009; Moussaïd et al., 2011). A third area of research focusses on how group formations both influence and are influenced by crowd flow (Vizzari et al., 2015). However, these approaches are yet to incorporate current developments in social psychology to address how large group members interact, and how they are influenced by the presence of another large group in counterflow. The present study investigates the impact of social identity on pedestrian behaviour when a large group walk on their own, and when two large groups with different group identities walk in counterflow. We examine how social identities affect self-organising behaviour to maintain close proximity to ingroup members through regulation of the speed and distance walked, when a) walking alone and b) when walking in counterflow to an outgroup.

Approaches to pedestrian behaviour

Numerous approaches have attempted to explain pedestrian behaviour in crowds. Some accounts have suggested that pedestrian behaviour in crowds is simply a derivative of the personalities or characteristics already present in individuals in the crowd. For example, a virtual evacuation experiment by Moussaïd and Trauernicht (2016) examined cooperation during emergencies based on personality types. Participants' personality types were measured based on their Social Value Orientation scores (Murphy et al., 2011), to assess how participants allocated resources between themselves and another person. During the simulation, participants were allocated rewards or penalties for helping other people escape an evacuation at varying levels of risk to the participants escaping safely themselves. Moussaïd and Trauernicht found that behaviour in emergency situations was due to participants' pre-existing tendencies of weighing up their chance of success if they helped others. This individualistic approach to crowds - where crowd behaviour is treated as a derivative of numerous individuals within the crowd without psychological connections to one another - is often used in computer models which employ principles from particle physics, such as social force models (for examples, see Gawroński & Krzysztof, 2011; Gutierrz, Frischer, Cerezo, Gomez, & Seron, 2007; Heliovaara, Korhonen, Hostikka, & Ehtamo, 2012). While these approaches are important to model crowds of individuals during ingress or egress scenarios, they reduce crowd flow and interactions between pedestrians to how individuals can best reach targets while manoeuvring around others. These approaches neglect the role of connections between pedestrians, and how groups acting together can influence crowd flow.

Other research has understood pedestrian behaviour as being a response to social information in the environment, such as how the perception of other people's behaviour can influence individual navigation through crowds. For example, research suggests that pedestrians self-organise to create walking lanes and follow pedestrians in front of them when in counterflow (Helbing et al., 2001) and choose the direction that will least decrease their speed (Moussaïd et al., 2009). Other examples include how pedestrians are influenced by where other pedestrians look and walk (Gallup et al., 2012; Helbing et al., 2000) and how quickly other pedestrians respond at the beginning of an evacuation (Chow, 2007; Purser & Bensilum, 2001; Nilsson & Johansson, 2009). A key study conducted by Bode, Wogoum, and Codling (2014) examined the role of information from other pedestrians in a simulated crowd experiment. They compared the influence of signs, the movement of other pedestrians, and previously memorised information about the environment. They found that the movement of other pedestrians and the memorised information did not have a significant effect on exit choice alone, but when the memorised information about the environment and the movement of other pedestrians were combined to be in contrast to the signs in the environment, the number of participants who followed the signs reduced. However, this research examines how individuals are influenced by the behaviour of others who they are unconnected to. They do not address the effect of pre-existing connections between crowd members, or how groups collectively self-organise within a crowd to move together.

One study which does investigate such group behaviour examines how groups create and maintain formations as they progress through a crowd. Moussaïd et al. (2010) analysed 1,500 pedestrian groups and suggest that group members will aim to walk side-by-side when in a crowd of low density, or a ‘V’ formation to ease communication as they progress through a higher density crowd. However, as the crowd density increases these formations can be broken to allow faster movement. A similar finding occurs in Köster et al. (2011) who found that students in an evacuation would try to walk abreast to enhance communication. This principle was extended by Vizzari et al. (2015) to analyse the effect of group size on pedestrian flow and formation. Vizzari et al. (2015) manipulated the size of the group to have pedestrians walk together in counterflow either as single pedestrians, pairs, a group of three, or a group of six, and found that pedestrian evacuation time was increased when the groups maintained their formations throughout the crowd.

Such analysis on the role of collision avoidance, social cues, and group formations have made important contributions to understanding pedestrian behaviour in crowds. However, these have predominantly dealt with individuals receiving social cues, or small groups walking through a crowd. They have not addressed the underlying factors that make a 'group'. Moreover, despite the regular occurrence of crowds in counterflow such as at fans at sporting events and music festivals, most research has looked at when small groups of people walk in counterflow. Little research has addressed what happens when two large groups come into counterflow, such as pedestrians at large sporting events going to different areas in an arena, and festival goers moving between different stages. One theory from social psychology that can help to understand the collective behaviour of large groups, and is based on extensive empirical research, is SCT (Turner et al., 1987).

Incorporating intra- and intergroup psychology

To understand large group behaviour, a useful distinction can be drawn between physical crowds and psychological crowds (Reicher, 2011). Physical crowds comprise individuals and small groups of friends or family members, for example crowds in shopping centres and transport hubs, who are simply in the same space together. Psychological crowds, however, are those where the members of the crowd share the sense of being in the same group; people who are part of such crowds act in accordance with their identity as a member of that group. Therefore a single physical crowd may contain none, one, two, three or more psychological crowds within it. SCT explains that when a person's identity as a member of that group (their social identity) is salient, a process of depersonalisation occurs where the individuals define themselves in terms of their social identity rather than their personal identity. It demonstrates how people categorise themselves and others into groups and how social identities can affect people's perceptions and feelings. One way that people understand their group identities is how much one perceives oneself to be similar to members of their ingroup compared to members of another outgroup. The meta-contrast principle (Turner, 1991) indicates that a group is more likely to be perceived as a group if the differences between ingroup members are smaller than the differences between the ingroup and outgroup members.

Research in this area has shown how shared social identities increased people's feelings of safety in dangerous crowd densities at the Hajj (Alnabulsi & Drury, 2014), mitigated perceptions of the cold at the Magh Mela festival (Pandey et al., 2014), and increased positive experience amongst festival goers, protestors, and football supporters (Neville & Reicher, 2011). Shared social identities can also influence the behaviour of crowd members. For example, during a free outdoor music event on Brighton beach, 2002, the crowd reached such a high density that emergency services were unable to enter the crowd. However, the shared social identity amongst the attendees led the crowd to self-organise to provide other group members – who were previously strangers - with water and coordinate their movement during egress to evacuate the beach safely (Drury et al., 2015). There is also evidence that a shared social identity led survivors of the July 7th 2005 London bombings to come together to apply first aid to one another and organise escaping safely in orderly queues in the absence of emergency services (Drury et al., 2009b). The effect of group identification on evacuation behaviour has also been demonstrated by Drury et al. (2009) using a virtual reality simulation. In this simulation, participants had to escape a fire in an underground rail station. Their research indicated that cooperation amongst participants increased among those who most highly identified with the group due to the shared fate induced by the evacuation, and this decreased competitive behaviour such as shoving and pushing during egress.

Crucially, social identity has also been shown to affect the maintenance of physical distance between people. Novelli et al. (2010) found that when participants defined themselves as being in the same group as another person in the room, the participants moved their chairs significantly closer together than if the other person was perceived to be a member of a different group. Overall, this research provides prima facie evidence that large groups with a shared social identity collectively self-organise their behaviour with ingroup members, and that people prefer to be closer to ingroup than outgroup members.

The Current Study

This study aims to examine the hypothesis from social psychology that people with a shared social identity will coordinate their behaviour with their ingroup to be closer to ingroup members over outgroup members. Specifically, we analyse pedestrian flow to determine how social identities affect the proximity between participants. Further, we utilise the meta-contrast principle to explore whether proximity is increased in the presence of an outgroup, and the consequences this has for pedestrian flow. Using a minimal group manipulation, we created two teams and explored their group identification and movement behaviour. We hypothesised that shared social identity will cause group members to, 1) regulate their speed and distance to remain together, and 2) regulate their behaviour to maintain closer proximity when in the presence of an outgroup.

Methodology

Procedure

Participants were selected based on their attendance of a second year Psychology lecture at the University of Sussex, and were recruited under the guise of participating in a study researching how people walk. Before leaving their lecture, participants were randomly allocated into team A (n = 28) or team B (n = 26) using a random number generator[2]. We used standard forms of social identity manipulation based on minimal group paradigms by priming participants to perceive themselves as being in different groups to get participants to

[2] Initially there were 28 participants in both teams, but two participants from Team B left before the first phase of the study.

discriminate on the basis of group membership (Haslam, 2004). To do this, we primed separate identities for the two teams with the aim of making their identities as team A or team B members more salient than any pre-existing bonds amongst the participants. After the participants exited the lecture theatre, research assistants instructed them to look at the tables on opposite sides of a courtyard. One table had a large 'Team A' sign, while the other table had a large 'Team B' sign, and participants were instructed to go to their allocated team table. Participants were given baseball caps as further identity primes; participants in team A were provided with black baseball caps with an 'A' logo on the front, and participants in team B were given red caps with 'B' logo on them. These identity primes allowed participants to perceive which team the other participants were in, and additionally enabled the researcher to allocate participants into the correct groups during the coding of the video data.

Group identity manipulation check

Prior to walking, participants were given questionnaires based on group identification measures from Doosje et al. (1995) to measure their identification with members of their own team (ingroup members) versus identification with members of the other team (outgroup members). First, participants were asked to declare which group they were a member of and name who the other group were. Participants were then asked to rate their level of identification towards their own team and the opposite team, using identical questions about their bond, affinity, and commitment towards each group on a Likert scale of 1 (not at all) to 7 (very much). The questions were; '*I feel a bond with the people in this group*', '*I feel an affinity with this group*', and '*I feel committed to this group*' (the full questionnaire is provided in Appendix 1).

Behavioural data

The research took place at the University of Sussex on a main pathway through the campus. Filming was conducted with a Nikon PixPro AZ361 digital camera with a 36x wide

24-864mm equivalent Aspheric HD Zoom Lens with no zoom or lens distortion, and took place from a low bridge above the path the participants walked along to enable object tracking of their movement. A section of the path (length = 10 metres, width = 3.75 metres) was selected as it was wide enough for the two teams to walk in counterflow without reaching a dangerous density. This path serves as the main route between their lecture where the study began, and two areas at opposite ends of the path where participants were asked to walk to (please see Figure 11 for a map of the locations, where the area that was filmed is indicated by the dashed line).

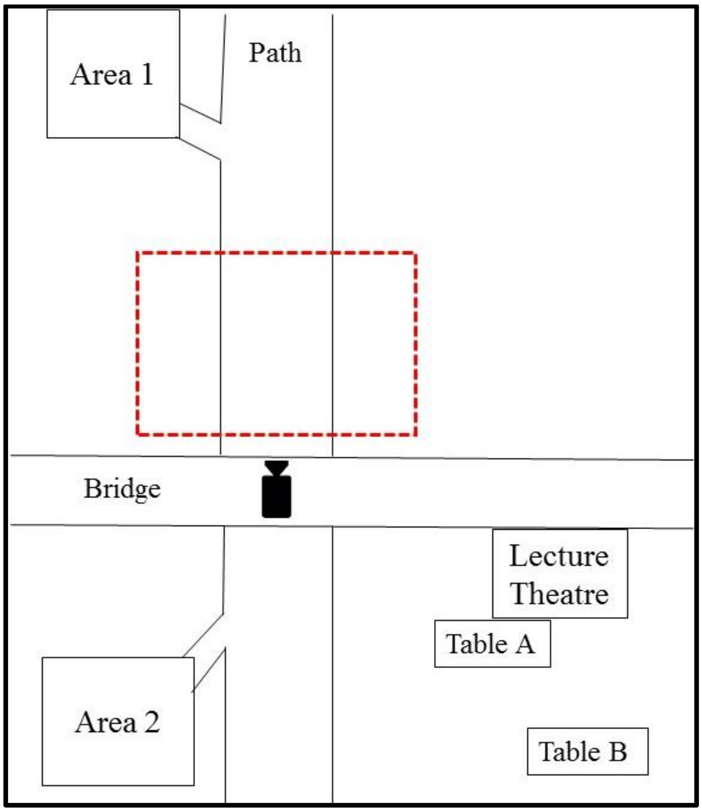

Figure 11: Map of area (not drawn to scale).

Behavioural data was collected in three phases. In the first phase, team A were given the instruction ‘people who are in team A, please walk to [Area 1] where you will be met by a research assistant who will give you further instructions'. When team A arrived there, the assistant sent them to Area 2 on the other side of campus which enabled the experimenters to film team A walking along a pathway without any other groups present. This data provided a comparison of how the team walked when sharing a social identity but when they were not in counterflow with another group who shared a different social identity.

In the second phase, once team A had arrived at their destination, participants in team B were given the instructions 'people who are in team B, please walk to [Area 1] where you will be met by a research assistant who will give you further instructions'. This location was chosen as it positioned team A and team B on opposite sides of the bridge where filming was conducted.

In the final phase, the research assistants instructed team A to walk back to Area 1 and team B to walk to Area 2. To reach their destinations, the participants would need to walk along the main path at the same time from opposite directions, meaning that they would be in counterflow. When the teams walked in counterflow, 4 pedestrians walked the same direction as team A and 1 pedestrian walked in the same direction at team B. These extra pedestrians were not included in the analysis for speed or distance, but were included when using the number of people present in the area as a predictor of the proximity between pedestrians.

Due to the density of the groups and the angle of filming from the bridge, it was not possible to ascertain the feet positions of the participants. Instead, the positions of the pedestrians' heads were identified using MATLAB software to manually mark the coordinate positions of the participants every 5 frames (frame rate 24 frames per second, approximately 1/3 of a step) to reconstruct their trajectories as they walked along the pathway. The data was transformed from the camera angle to a directly top-down planar view to assess the location of the pedestrians on the ground. The transformations were calculated using the corners of a

3.75 metre by 5 metre rectangle painted on the pathway, assuming the participants had a constant height of 169 cm (taken as the midpoint between the average heights of men and women in the UK). This leads to potential error both from height deviations from the assumed height, and from swaying of heads of the participants walked. The median and interquartile ranges were 21 +/- 14cm for both crowd conditions (the camera did not move between the conditions where team A walked alone and when teams A and B walked in counterflow). Importantly, the differences were consistent across the participants, so they do not affect measures of speed and distance travelled.

Speed and distance of movement

The positions of the participants' feet were used to ascertain the distance walked, speed of movement, and the proximity between individuals. Distance was calculated in MATLAB by summing the distance between the coordinates of each projected location. The speed was calculated as speed = distance/time (time = 0.2085 as 1 second/frame rate * 5 for the frame gap). The speed and distance were measured for team A when walking alone, and both team A and team B when walking in contraflow to determine whether there was a difference in speed and distance when the team A walked alone and when they walked in counterflow.

Proximity between ingroup members

To ascertain how much space individuals maintained around them, a snapshot of the pedestrians' projected locations was taken every 4.17 seconds (100 frames) to produce the positions of the pedestrians at eight time points. The space around each pedestrian was calculated using Sievers's (2012) method for Voronoi decomposition, with the tessellation areas given an upper bound of 1 metre to avoid inflating the space around individuals walking on the periphery of the groups. Following this, Latent Growth Curve Modelling was used to determine whether 1) group membership was a predictor of tessellation areas over three time points in the counterflow condition, and 2) the number of people present in the area at different time points predicted the tessellation areas by using the number of people present as a time-varying covariate.

Results

Manipulation checks

A 2x2 mixed design ANoVA showed that ratings of identification were significantly higher towards the ingroup (team A: M = 3.13, SE = 0.28; team B: M = 2.96, SE = 0.27), than towards the outgroup (team A: M = 1.91, SE = 0.17; team B: M = 1.49, SE = 0.17), $F(1)$ = 69.73, p < .001. The difference in ratings of identification given by team A and B were non-significant, $F(1)$ = 0.64, p = .427, indicating that both groups rated higher identification towards the ingroup than the outgroup.

Speed and distance

Kolmogorov-Smirnov tests revealed that when team A walked alone neither their speed or distance deviated significantly from normal. In the counterflow condition, neither the speed of team A or B deviated significantly from normal, however, the distance of both teams were non-normal. When examining tessellation areas across the eight time points, the tessellation areas of team A were normal when walking alone, but tessellation areas for team A and team B in counterflow were non-normal (see Table 3 for D-values, degrees of freedom, and p-values).

Independent t-tests revealed that team A walked significantly faster when walking alone (M = 111.94, SE = 1.41) than they did when walking in counterflow (M = 57.91, SE = 0.76), 54.03, BCa 95% CI [50.79, 57.27], $t(51)$ = 33.73, p < .001, r = .978. They also walked significantly further when alone (M = 937.18, SE = 7.75) than when in counterflow (M = 520.52, SE = 4.78), 416.66, BCa 95% CI [403.12, 430.21], $t(51)$ = 61.77, p < .001, r = .993. Together, these results suggest that the speed of movement and distance both decreased in the presence of an outgroup.

Table 3

The D-values, degrees of freedom, and p-values for speed, distance, and tessellations areas of groups in each condition

	Speed			Distance			Tessellation areas		
	D	df	*p*	*D*	df	*p*	*D*	df	*p*
Team A alone	.11	27	.200	.12	27	.200	.08	77	.200
Team A counterflow	.08	26	.082	.20	26	.008	.12	112	.001
Team B counterflow	.17	26	.060	.19	26	.013	.15	115	.001

In the counterflow condition, an independent t-test showed team A (M = 57.82, SE = 0.79) walked significantly faster than team B (M = 55.52, SE = 0.81), 2.30, BCa 95% CI [0.031, 4.57], $t(50)$ = 2.04, p = .047, r = .276. A Kruskal-Wallis test showed that there was a non-significant difference in distance walked between the different teams (team A: *Mean rank* = 32.60; team B *Mean rank* = 27.53), $\chi^2(1)$ = 1.45, p = .229.

Table 4

Means and standard deviations for team A and team B

	Speed (metres per second)		Distance (metres)		Tessellation Areas (cm^2)	
	Mean	SD	Mean	SD	Mean	SD
Team A	57.82	4.01	519.79	25.05	9246.14	5546.68
Team B	55.52	4.13	519.06	17.80	7791.71	5647.99

Tessellation areas

Kolmogorov-Smirnov tests revealed that the tessellation areas of team A when walking alone were normal across the eight time points, but the tessellation areas for team A when walking alone and team B were non-normal across the 5 time points (see Table 3 for *D*-

values, degrees of freedom, and *p*-values). As such, a Kruskal-Wallis test was used and revealed a significant difference between the tessellation areas of team A when alone (*Mean rank* = 116) than when in counterflow (*Mean rank* = 55.38), $H(1) = 65.67$, $p < .001$, providing support for Hypothesis 2 that team A members maintained closer proximity in the presence of team B (see Figure 12 for a snapshot of team A in both conditions, where the heads of team A are depicted in purple dots and team B in red dots). Moreover, team A (*Mean rank* = 123.71) had significantly greater tessellation areas than team B (*Mean rank* = 104.55), $H(1)= 4.83$, $p = .028$ when walking in counterflow (see Table 4 for a comparison of means, standard deviations and test statistics for each group).

Latent Growth Curve Modelling was used to ascertain 1) whether group was a predictor of tessellation areas across three time points, and 2) the effect of the number of people in the area on the tessellation areas. Due to participants walking through the footage, each participant was present for approximately three-points of total eight time points. As such, we used the tessellation areas of participants from when their first tessellation area was calculated (Time 1), and their tessellation areas at the following two time points (Time 2 and Time 3). The intercept was weighted as 1 on each time point to constrain them as equal. The slope was weighted on the time points as Time 1_0, Time 2_1, and Time 3_2, as the times were equally spaced at 4.17 seconds apart. The intercept and slopes were extracted across Time 1, Time 2, and Time 3, and used as estimates of (a) baseline tessellation areas before coming into contact with the outgroup (Time 1) and (b) increase or decline in tessellation areas across the successive time points when the groups are in counterflow. To determine whether the number of people predicted tessellation areas, we used the number of people in the area at each time point as a time-varying covariate with the corresponding tessellation areas of the participants at those time points. Group was regressed onto the intercept and slope, and participants were coded in their relevant groups (team A = 1, team B = 0). Robust maximum likelihood was used due to the non-normal distributions of team B, and we chose full information maximum-likelihood (FIML) as there were 5 missing data-points across Time 2 and Time 3 due to people moving outside the parameters of the footage.

(a) (b)

Figure 12: Snapshots from footage from (a) team A walking alone compared to (b) when team A and B walk in counterflow.

We used the criteria suggested by Hu and Bentler (1999) to assess model fit, where the model fit is based on RMSEA < 0.06, SRMR < 0.08, CFI > 0.95. This led us to consider our model provided overall adequate fit, RMSEA = 0.07, SRMR = 0.07, CFI = 0.98, with a non-significant chi-square, $\chi^2(15) = 9.05$, $p = 0.249$. In the model, the number of people was a non-significant predictor on tessellation areas at Time 1, β = -0.849, $p = .073$, but a significant predictor at Time 2, β = -0.253, $p < .001$, and Time 3, β = -0.387, $p < .001$, indicating that the tessellation areas were influenced by the overall number of people in the area, providing support for Hypothesis 2 (for path diagram, see Figure 13). As can be seen in Figure 14, the tessellation areas decrease as the number of people in the area increase, indicating that participants move closer to the ingroup when in the presence of an outgroup. In Figure 14, tessellation areas are taken from each pedestrian's first occurrence in the footage (Time 1) and subsequent two time points (Time 2 and Time 3). The x-axis denotes the data binned between ranges of people present to show mean tessellation areas as number of people present in the area increases. The means and standard deviations for each group across all eight time points and corresponding number of people in the area are presented in Table 5.

Using group as a predictor on the intercept revealed that the groups have significantly different initial tessellation areas at Time 1, $\beta = 0.550$, $p < .001$, with people in team B having larger initial tessellation areas (see Figure 14). Group was also a significant predictor of change over time, $\beta = -0.849$, $p < .001$, indicating that the change of tessellation areas over time were different for the groups when including the number of people in the area. The number of people present in the area was a non-significant predictor of tessellation areas at Time 1, $\beta = -0.163$, $p = .073$, but was a significant predictor of tessellation areas at Time 2, $\beta = 0.253$, $p = .007$, and Time 3, $\beta = .387$, $p < .001$. However, as can be seen in Figure 14, the tessellation area for both groups decreased in the presence of the outgroup overall.

Combining speed, distance, and proximity

In summary, when walking alone, team A maintained close proximity with ingroup members, walked faster, and walked further. In the contraflow condition, team A maintained closer proximity and reduced their speed and distance. This provides support for Hypothesis 1 that participants regulated their movement and speed to remain together, and Hypothesis 2 that the participants regulated their speed and distance walked to maintain a closer proximity with ingroup members when outgroup members were present. Although we could not obtain data of team B walking alone, Figure 16 demonstrates that the distance, speed, and tessellation areas of both team A and B in counterflow were less than Team A walking alone, tentatively suggesting that team B were also affected by the presence of another group counterflow.

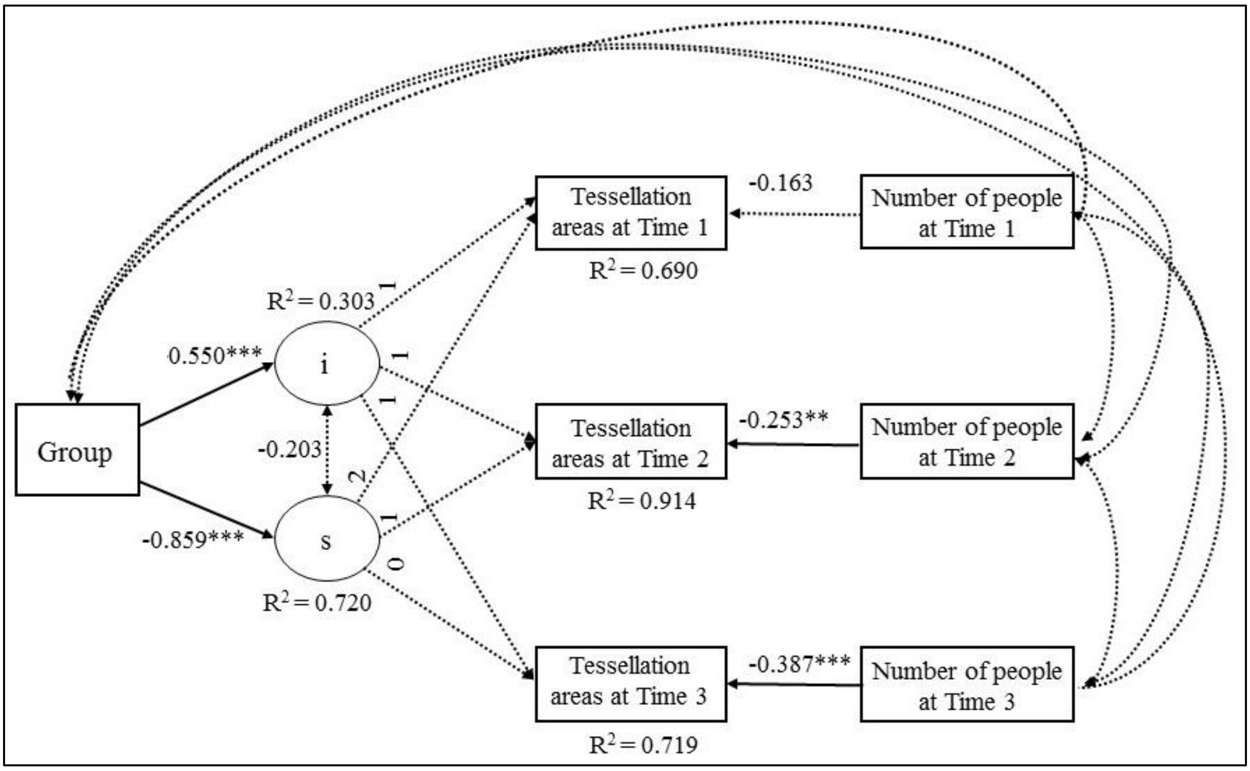

Figure 13. Path diagram depicting results for Latent Growth Curve Modelling with standardised estimates indicating tessellation areas as a function of group and number of people in the area. Solid lines indicate significant pathways, and dotted lines indicate non-significant pathways (**p* < .05, ***p* < .01, ****p* < .001).

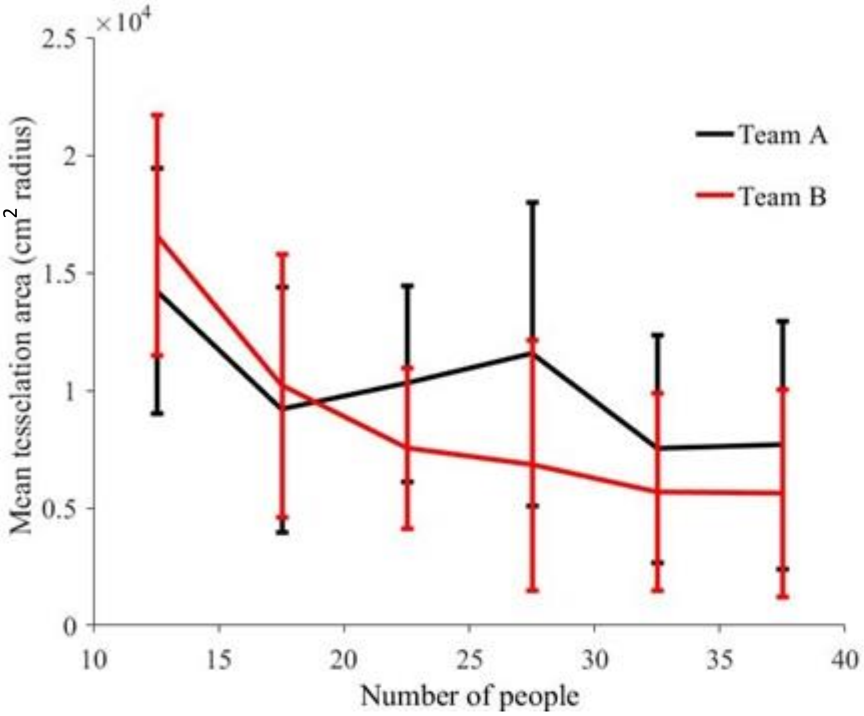

Figure 14: The mean tessellation areas and standard deviations for team A and team B used in the Latent Growth Curve Model.

Table 5

The mean tessellation areas and standard deviations for both teams as the number of people in the area increases

		Number of people in the area							
		15	20	21	23	23	28	30	34
Team A	Mean	10276.31	10444.21	10274.28	9725.41	10837.26	6293.34	7800.33	6355.74
	SD	5823.80	5186.01	4426.48	7318.68	4642.58	5283.16	4680.84	4603.63
Team B	Mean	8996.22	7968.93	7681.54	7301.19	7035.53	6278.72	5462.18	5615.28
	SD	6218.25	4006.80	3397.70	6309.65	5026.07	5669.84	4387.73	4405.69

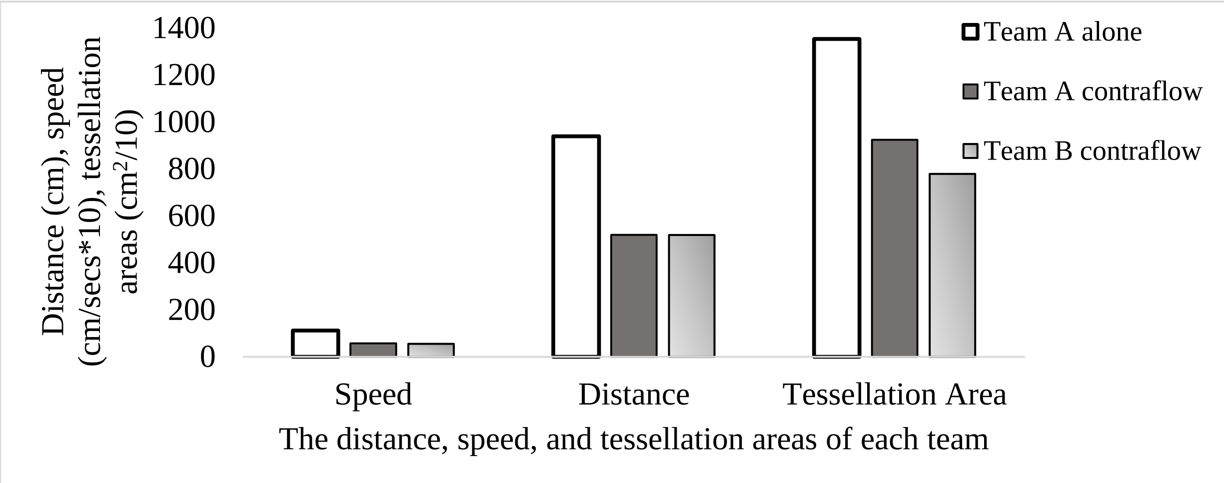

Figure 16: The speed, distance, and tessellation areas of team A walking alone, team A walking in counterflow, and team B walking in counterflow.

Discussion

This study suggests that social identity motivated large groups to self-organise to remain together, that this was increased by the presence of an outgroup, and that this influenced pedestrian flow when in counterflow with others. The manipulation check found that participants reported higher identification with members of their ingroup than the outgroup, which supports the suggestion that it was the social identity manipulation, and not another factor, that led to some of the behaviours observed. Specifically, shared social identity had three key behavioural effects. First, having a shared social identity caused the participants to self-organise to walk together, as can be seen by the proximity of team A members to each other when walking alone. Second, the presence of a group with a different social identity enhanced this behaviour as participants moved closer to one another in order to stay together as a group. The slower speed and reduced distance walked by team A when walking in counterflow compared to walking alone indicates that participants prioritised remaining together over easing pedestrian flow. Notably this occurred on quite a narrow path of 3.75 metres in width that was surrounded by grass that they could walk on. Participants could have chosen to move through the crowd more quickly by splitting in to smaller groups, or even moving as individuals. Instead, participants regulated their behaviour in order to keep formation as a group on the path, electing to stay two, three, or four people abreast and move closer together.

The attempt by participants to remain with team members supports the formations found in the low density crowds reported by Moussaïd et al. (2010), but instead of breaking up in higher densities, participants maintained their formations even as the number of people in the area increased. The participants attempted to stay abreast while walking, replicating the formations found by Köster et al. (2011), and decreased their speed in order to stay together, repeating the small group behaviour found in Vizzari et al. (2015). The fact that participants with a shared social identity did not split up appears to be inconsistent with much research in pedestrian flow. For example, the participants did not form the multiple single lanes found by Helbing et al. (2001), instead electing to create two large lanes to stay together. Moreover, in contrast to Moussaïd et al. (2009), they did not choose the direction of movement which would least decrease their speed, instead prioritising staying with ingroup members. These findings suggest that when considering pedestrian counterflow in crowds, research should consider that groups with a shared social identity prioritise staying together even when it impedes their speed.

There are potential limitations to this study pointing to avenues for future research. Due to the angle of filming from the bridge, it was only possible to capture a section of the path where the groups were already only six metres away from coming into contact. This meant that participants were already in the process of manoeuvring to take over a section of the path compared to the outgroup. Future research should aim to examine behaviour beginning from a point when they are further apart. Moreover, this path was quite narrow and the participants may have perceived the edge of the path as a barrier instead of walking on the grass. Future research should examine proximity and formations when there is more space available for the pedestrians to move in. Although there were only five additional pedestrians to our primed participants in the counterflow condition, ideally other pedestrians would not have been present to evaluate how the teams interacted solely with one another. In this study we were unable to obtain footage of Team B walking alone to compare their behaviour to the counterflow condition, thus having to compare Team A in both conditions only. Future research would benefit from replicating this study where both groups are filmed prior to walking in counterflow, in order to compare how the presence of another group influenced their behaviour more thoroughly. Finally, we analysed 61 participants across three time points for Latent Growth Curve Modelling. Although there is debate about the optimum number of participants needed to reliably estimate growth models (see Curran, Obeidat, & Losardo, 2010, for an overview), this is dependent upon the complexity of the model and variance explained by the model. Our model indices imply that the model was an adequate fit, but future research using Latent Growth Curve Modelling should aim to have more participants for increased reliability.

Large psychological groups and psychological crowds who move on their own or in contraflow are a common occurrence in mass crowd events. For example, ingress and egress of fans at a concert, festival-goers moving to different stages, sports fans of opposing teams entering or leaving a stadium, protests and counter-protests, large groups travelling to and from these events at transport hubs, and emergency evacuations. Often, these psychological groups and crowds are present within a larger physical crowd. The present study indicates that sharing a group identity causes ingroup members to collectively self-regulate to walk together. Moreover, this effect is increased when in the presence of another psychological group in counterflow, leading participants to decrease their speed in order to remain together and maintain their formation. This is contrary to the research of Helbing et al. (2001) and

Moussaïd et al. (2009) which suggests that groups split up to improve crowd flow; in our experiment participants with a shared identity prioritised staying together over moving quickly. In order to adequately plan for crowd safety, modellers and safety practitioners should consider the behavioural differences between physical crowds and psychological crowds. Crucially, they should incorporate how people with a shared identity prioritise moving together over easing crowd flow, and how this can affect the ingress and egress of both psychological crowds on their own, and psychological crowds within physical crowds.

Chapter 5

Paper 4 - Incorporating self-categorisation into a computer model of crowd behaviour

Reference:

Templeton, A., Drury, J., & Philippides, A. (Submitted to Scientific Reports). Incorporating self-categorisation into a computer model of crowd behaviour.

Abstract

Computer models are used to simulate crowd behaviour for safety at mass events. However, these models are often based on incorrect assumptions that crowds behave simply as individuals or consist only of small groups. SCT has suggested that there are differences between *physical* crowds of unconnected individuals, and *psychological* crowds whose collective behaviour is based on a shared social identity. Research into behavioural effects of self-categorisation has demonstrated that pedestrians in a psychological crowd collectively self-organise to maintain close proximity to ingroup members, which requires regulation of their walking speed and distance to move as a large group. As yet, no computer model has incorporated how large crowds regulate close proximity based on their shared social identities. Moreover, popular approaches to crowd modelling are limited in how realistically they can simulate dense crowds due to either high computational load or limited capacity for agent navigation. We present the first attempt to introduce principles of SCT into a computer model of collective behaviour based on empirical data on crowd movement. Using the OSM, we incorporate a self-categorisation parameter that attracts pedestrians to ingroup members. We validate the model by comparing the speed, distance, and proximity of pedestrians to footage of a crowd who i) walked without having social identities primed (physical crowd), and ii) walked when primed to share a social identity (psychological crowd). We discuss the implications of incorporating SCT into computer models of psychological crowds to simulate collective behaviour, and the importance of understanding social identities for crowd safety planning.

Introduction

Computer models of collective behaviour provide a key tool for planning and monitoring pedestrian behaviour at crowd events, including crowd flow during ingress and egress at transport hubs, concerts, sporting events, and behaviour during emergency evacuations. Two main approaches have been used to model crowd flow: force-based models in continuous space (e.g. Langston et al., 2006; Zeng, Chen, Najamura, & Iryo-Asano, 2014) and cellular automata (e.g. Dijkstra, Jessurun, & Timmermans, 2001; Kirik, Yurge'yan, & Krouglov, 2007). These approaches use repulsion potentials to simulate the role of navigation in collision avoidance while being attracted to a target during ingress and egress. However, social force models require high computational effort, and cellular automata often have limited capacity for the acute steering required for pedestrians in large groups. Moreover, a systematic review of the crowd modelling literature by Templeton et al. (2015) found that crowd models rarely address the underlying principles of what makes a 'group' or 'crowd'. Modellers simulated crowds where pedestrians either behaved as a homogeneous mass, acted as individuals without connections to one another, or consisted of small groups with varying levels of inter-personal social connections. These models did not distinguish between *physical* crowds acting as individuals or small groups of people, and *psychological* crowds (Reicher, 2011) who collectively self-organise their behaviour due to a sense of being in the same social category. One theory that can explain the basis of these psychological differences, is SCT (Turner et al., 1987).

Research based on SCT has indicated that group behaviour can be understood through shared social identities. For example, SCT has demonstrated that people will sit in closer proximity to unknown people who are perceived to be ingroup members than outgroup members (Novelli et al., 2010), and how members of a crowd who perceived others as ingroup members coordinated their actions for safe egress from a music event (Drury et al., 2015). Recent research by Templeton et al. (in preparation) indicates that social identities can also influence pedestrian movement in crowds. They compared the walking behaviour of a physical crowd comprised of individuals and small groups in the same place at the same time, and a psychological crowd where most of the people present in the physical crowd were primed to share a social identity. Comparisons between the crowds suggest that a shared social identity motivated psychological crowd members to collectively self-regulate to maintain close proximity with ingroup members while walking, causing them to reduce their speed and walk further to remain together. Importantly, the collective self-regulation to obtain close proximity in large groups was not found in the physical crowd scenario.

The behavioural differences between physical and psychological crowds have important implications for computer models of pedestrian flow that implement navigation primarily through repulsion potentials and attraction to targets. It suggests that these models are missing a key element for modelling the collective behaviour of psychological crowds: how self-categorisation causes attraction between ingroup members on a large scale, and how this attraction effects the speed and distance walked by crowd members. Based on the evidence of collective self-regulation in psychological crowds to maintain close proximity, computer models aiming to simulate psychological crowd flow should incorporate the importance of ingroup members regulating their speed of movement and distance walked to remain close together. Instead of simply modelling small groups within a larger physical crowd, these models should simulate the collective coordination of large groups within a crowd, or even the entire crowd acting as a group.

This paper aims to demonstrate the effect of social identities on crowd flow by incorporating the collective self-regulation behaviour found in the psychological crowd into a computer model of crowd movement. First, this paper will briefly address the theoretical and practical considerations for modelling large crowds where pedestrians share a category membership. Second, we present a pedestrian model of physical crowd behaviour based on collision avoidance through repulsion potentials. The speed of walking, distance walked, and proximity between pedestrians are validated against the behaviour of pedestrians in footage of a physical crowd. We then demonstrate that variations of the speed and repulsion potentials in the physical crowd cannot simulate the collective self-organisation to maintain close proximity that was found in footage of a psychological crowd, and therefore another factor is required to model psychological crowd behaviour. Third, we model the psychological crowd behaviour by introducing a self-categorisation parameter to the pedestrian model that incorporates principles from SCT to implement attraction potentials towards ingroup members. To validate the self-categorisation parameter, we adjust the attraction potentials between ingroup members and compare the model outputs of speed, distance and proximity to the behavioural data of a real psychological crowd. Finally, we discuss the implications of the self-categorisation parameter for simulating psychological crowd flow, and the importance of understanding social identities to safely plan for mass crowd events.

Theoretical considerations: The psychology of the crowd

Previous research has suggested that there are key psychological differences between physical crowds, which consist of small groups and unconnected individuals in the same space at the same time, and psychological crowds whose collective behaviour occurs through their shared social identity as members of the same group (Reicher, 2011). SCT (Turner et al., 1987) makes a distinction between personal identities, which refer to peoples' idiosyncratic differences from each other, and social identities that refer to peoples' conception of themselves as members of social groups. It suggests that social categorisation leads to the formation of psychological groups; a process of self-stereotyping leads individuals to shift from their personal identity to a salient social identity. Here, they perceive themselves as relatively interchangeable with ingroup members based on their similarity as members of the same group. Crucially, collective behaviour is possible when group members share social identity.

Research has found emotional and behavioural effects of shared social identities on crowd members in numerous mass events. For example, a sense of relatedness through shared social identities was found to influence positive emotions at sporting events (Stott et al., 2001) and protests (Neville & Reicher, 2011). Moreover, Novelli, Drury, Reicher, and Stott (2013) indicated that when people identified with the crowd they perceived a music event and protest demonstration to be less crowded and subsequently had increased positive emotions. Together with the findings of Novelli et al. (2010) that participants sit in closer proximity to ingroup members, the effect of social identity on perception of crowdedness suggests that physical models of crowd behaviour where pedestrians avoid dense crowding may not apply to crowds that share a social identity.

More recently, Templeton et al. (in preparation) indicates that social identity also affects the underlying movement of crowds and subsequently pedestrian flow. A physical crowd was filmed walking along a path between two locations, and the same participants were also filmed walking in the same location after being primed to share a social identity (psychological crowd scenario). The coordinates of the pedestrians were tracked as they walked through the footage, and their speed of movement, distance waked, and the proximity between members were measured. In the physical crowd, pedestrians walked either as individuals and maintained more space around themselves when navigating around others, or in groups that were limited to a maximum of four people who moved through the area together. In the psychological crowd, the pedestrians collectively regulated their behaviour to walk in close proximity with ingroup members, subsequently decreasing their walking speed and increasing their distance to maintain formation.

The findings of Templeton et al. (in preparation) imply a different behaviour from the assumptions that are implemented in current movement models. Rather than pedestrians walking as a mass of unconnected people or walking simply in small groups, it suggests that pedestrians in psychological crowds self-regulate their behaviour to maintain close proximity, and this can be applied to an entire crowd regulating their behaviour to walk together. We propose that computer models can improve their simulations of collective behaviour by incorporating principles of SCT. First, models should be able to provide pedestrians with a social identity to create a psychological group. Second, pedestrians should have the ability to know the social identity of others, so that they can coordinate their behaviour with fellow ingroup members. Third, to simulate the attempts of pedestrians with a shared social identity to stay close to ingroup members, models should include the ability for pedestrians to collectively self-organise their movement relative to the positions of other ingroup members so that they can remain together.

While recent approaches to crowd modelling have successfully simulated aggregates of people in the same area (e.g. Moussaïd et al., 2011) and small group behaviour in crowd flow (e.g., Köster et al., 2011; Moussaïd et al., 2010), as yet only one model has incorporated aspects of social identity into a simulation of crowd behaviour. Von Sivers et al. (2016) quantified and formalised research by Drury et al. (2009) which examined accounts by survivors and witnesses of the July 7th 2005 London underground bombings. Drury et al. found that survivors reported being strangers prior to the attack, but developed a shared social identity due to their shared fate during the bombings. Crucially, this shared identification caused survivors to help others in the group to evacuate, even at risk to their own safety. Instead of usual egress models which focus on people escaping as individuals or moving as small groups, von Sivers et al. introduced principles from SCT to implement the behaviour of helping injured ingroup members to evacuate. This was an important first step to introducing social identities into a computer model, but as von Sivers et al. note, this is based on self-reports of behaviour and cannot be validated with behavioural data. Real-world and experimental behavioural data are increasingly being used to validate pedestrian models (e.g. Kretz, Grunebohm, & Schreckenberg, 2006; Lerner, Chrysanthou, & Lischinski, 2007; Seyfried et al., 2009), but despite the behavioural differences between physical and psychological crowds, no model has been validated using empirical behavioural data from crowds who were primed to share a social identity.

Practical considerations

There are two key practical requirements for simulating psychological crowd behaviour. First, it must have the capacity to simulate both low densities for physical crowds and high densities of psychological crowds who walk in close proximity with ingroup members. Second, it must incorporate acute steering in reaction to fellow group members and others so that the crowd can collectively self-regulate their movement in high densities. Social force models - inspired by Newtonian mechanics and granular flow - model pedestrian steering as a function of attraction and repulsion forces (for an example of such models, see Helbing & Molnar, 1995; Moussaid et al., 2011). In these models, pedestrians are attracted to targets while being repelled by other pedestrians and obstacles in continuous space and time, and acceleration is treated as a function of friction between the attraction and repulsion potentials. This approach, however, requires high computational effort when simulating large crowds, and poses difficulties when predicting behaviour of sparse crowds without introducing additional features such as repulsive forces on the ground to guide more realistic navigation. As Dietrich et al. (2014) note, social force models can lead to inertia and pedestrian overlapping which can only be reduced by introducing extra parameters, leading to overly complex models.

Cellular automata are also based on attraction and repulsion forces but use floor-fields based on discretised cells where pedestrians step from cell to cell. The floor-field can be adapted to create more realistic pedestrian movement, such as by using different cell shapes (e.g. Chen, Barwolff, & Schwandt, 2014), or smaller cells where pedestrians can occupy multiple cells at once (e.g. Guo & Huang, 2008), but ultimately the direction of stepwise movement is limited to the structure of the floor-field. The restricted orientation of pedestrians around the environment poses difficulties for simulating movement in dense crowds, as pedestrians may require more acute options of movement to progress forward and avoid inertia (for a fuller overview of the limitations of cellular automata, see Craesmeyer & Schadschneider, 2014; Steffen & Seyfried, 2010).

One model that has the potential to provide acute navigation for both sparse and dense crowds at low computational effort, is the OSM (Seitz & Köster, 2012). The OSM combines the rule-based approach of stepwise movement from cellular automata without the restrictions of a cellular grid. Is uses discretised space locally on a step-circle around each pedestrian which dictates where the pedestrian can move to, but allows for individual free-flow in continuous space rather than being on a pre-defined grid. The OSM lends itself to high density crowds as steering is based on a step-circle around the pedestrian which has multiple optional step positions that can potentially be moved to (see Figure 17 for a diagram of the OSM step-circle, based on Seitz & Köster, 2012). Navigation is based on attraction to targets while being repulsed by obstacles, but acute steering in dense crowds is achieved by having the radius of the circle as the maximum stride length. Pedestrians can also move less distance than the maximum size of the allocated step circle, to allow for smaller steps if a smaller step is the optimal choice. This also lends itself to sparse crowds by adjusting the repulsive potentials of pedestrians and obstacles to enhance realistic navigation. In the study reported here, we use the OSM as our pedestrian model to simulate psychological crowds due to its flexibility to alter attraction and repulsion potentials for pedestrians, targets, and obstacles, and its ability to realistically simulate movement in both sparse and dense psychological crowds.

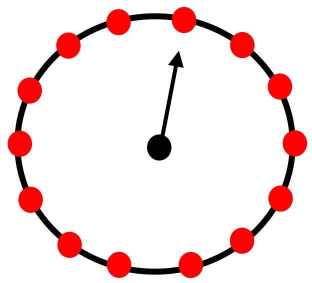

Figure 17: The OSM step-circle. The black circle demonstrates the maximum step length of the pedestrian, and the red dots indicate 14 potential directions of movement.

Methodology: The model

Agent navigation

Following the OSM, the direction of agents was determined by 14 equidistant positions on the step-circle radius around each pedestrian to allow acute steering in high densities. Each step choice was a function of the aggregated potential at each point on the step circle to find the optimal direction between attraction to the target and repulsion from obstacles and other pedestrians. Here, the more repulsive the potential of a position, the higher the value. The point that was closest to the target was denoted by zero, which allowed the agent to calculate the lowest utility using an optimisation algorithm to determine the best route given fourteen potential directions on the step-circle. Each agent had an assigned maximum step length of 0.7 metres on a radius around the agent. This number of optional directions and the ability to vary step length allowed for finer navigation in dense crowds while not requiring heavy computational load. To avoid pedestrians overlapping, we employed the repulsion potentials set by the OSM to be equal to the body lengths of the agents to prevent them from colliding.

According to Köster et al. (2011), the OSM allows each pedestrian to be driven by their fixed desired maximum speed and step-length, combined with the direction of the pedestrian in relation to their target and obstacles. The OSM is particularly appropriate for dense crowd situations because the speed and step-length can decrease if the pedestrian is obstructed. The OSM uses Sethian's (1996) Fast Marching algorithm on a two-dimensional grid to compute the floor field for targets and obstacles. We include pedestrians themselves as targets when they share a social identity, or obstacles when there was not a shared social identity. A priority queue was updated sequentially to avoid collisions, where the first agent generated was the first agent in the queue and so moved first. The model updated at the end of each iteration of the queue to allow all pedestrians an opportunity to move.

Implementing aspects of self-categorisation

A set of theoretical criteria are needed to implement some principles of SCT in a computer model that simulates some behavioural effects of shared social identities in pedestrian flow. First, the model must allow agents to have social identities and to know their social identities in order to be members of social groups. This can be either one social identity for the entire crowd or multiple psychological crowds within a larger physical crowd to simulate the behaviour of different groups. Second, it necessitates instantiating the perceptual abilities for each agent to recognise the identities of other agents to perceive whether they are ingroup or outgroup members. This is necessary for the agents to orientate their behaviour according to group membership and allow ingroup members to be attracted to one another.

Computer models which treat the crowd as homogeneous agents who merely avoid collision with one another cannot realistically implement a psychological crowd whose agents are motivated to regulate their behaviour to move together based on their shared social identities. In our model, we used agent-based modelling to allocate each agent an identity, and the ability to perceive the identities of other agents to determine who was a member of their group. The user could assign a specified number of pedestrians to share a social identity so that those agents are motivated to move together, and the user could create a number of groups with different social identities for each simulation. Although not used in this study, this would allow the creation of numerous scenarios, from individuals acting independently, to small groups, to where the entire crowd shared a social identity. In this study, we demonstrated two crowd scenarios to show the influence of self-categorisation on pedestrian flow: a physical crowd of unconnected individuals, and a psychological crowd who shared a social identity.

In the physical crowd model, each pedestrian was allocated a separate identity so that they navigated through the path while avoiding collision with other pedestrians. In the psychological model pedestrians were allocated the same social identity. To instantiate the tendency to maintain close proximity between ingroup members found by Novelli et al. (2010) and Templeton et al. (in preparation), the self-categorisation parameter rendered attraction potentials towards ingroup agents while the agents navigated towards a target. Thus, the self-categorisation parameter caused them to act according to their group membership when interacting with others to remain close to ingroup members.

Attraction to other pedestrians was dependent on the pedestrians being able to ‘detect’ another pedestrian within a fixed radius of themselves. Crucially, in the psychological crowd condition of Templeton et al. (in preparation), the attempt of participants to walk together resulted in reduced walking speed and walking a further distance due to acute navigation in the close density. The OSM is appropriate to model this as the walking speed of each agent can decrease depending on the agent’s ability to move at the desired speed. Thus, we hypothesised that in the psychological crowd simulation, the self-categorisation parameter which attracted ingroup members to one another would replicate the reduced speed and increased distance exhibited in the real psychological crowd behaviour.

Validation procedure

The simulation results for speed of movement, distance walked, and proximity between agents were validated by comparing them with the behavioural data of the physical and psychological crowds in Templeton et al. (in preparation) (see Table 6 for the mean speed, distance, and tessellation areas of the real crowds). Following the methodology used by Templeton et al., the speed of agents in the simulation was calculated as speed = distance/time, where distance was calculated by summing the distance between the coordinates of each agents' steps. The proximity between agents were calculated using Sievers' (2012) method for Voronoi decomposition which calculated the space around agents based on the proximity to their neighbours. In the real footage, the participants walked along a path but were only filmed as they walked along a 10 metre segment towards the camera. To keep the model as consistent as possible with the conditions in the footage, we used lines as obstacles to replicated the width of the pathway that the real pedestrians walked along (3.75 metres), and had the agents walk in an arena 50 metres in length but recorded their data within an allocated segment of 10 metres. The agents were randomly generated at the top of the path, and each agent was allocated the same target at the bottom of the path to replicate the direction of the pedestrians, and agents navigated along a path towards the target while they negotiated movement around other pedestrians in the area. This is conducted in two versions of the model; a) a physical crowd of unconnected individuals (N = 66) using repulsion potentials, and b) a psychological crowd where every member shares a social identity (N = 66)[3] and is attracted to ingroup members.

[3] In the study by Templeton, Drury, and Philippides (in preparation), there were 66 pedestrians in the physical crowd, and 112 in the psychological crowd. In this study, 66 pedestrians are used in both conditions for consistency, to demonstrate that the effects on speed, distance, and tessellation areas are not due to different numbers of people.

Table 6

The mean speed, distance, and tessellation areas obtained in the behavioural data of Templeton et al. (in preparation)

	Speed (metres per second)	Distance walked (metres)	Tessellation area (cm^2)
Physical crowd	1.10	7.80	20506.39
Psychological crowd	0.89	14.13	10383.29

(a) *Physical crowd*

The physical crowd in Templeton et al. (in preparation) walked 1.10 metres per second and the psychological crowd walked 0.89 metres per second. As such, we ran simulations with maximum walking speeds from 0.5 metres per second in increments of 0.3 to 1.7 metres per second. For each maximum walking speed, we examined the effect of corresponding repulsion distributions ranging from 0.5 metres (the body width of agents) in increments of 0.5 metres to two metres radius around the agents, and the height of the repulsion also ranging from 0.5 metres to two metres. We compared the effects of maximum walking speed and repulsion potentials on the mean tessellation areas, distance, and speed and determine which version of maximum speed and repulsion potentials best captured the speed, distance, and tessellation areas of the real physical crowd.

One potential argument against incorporating a self-categorisation parameter to simulate the psychological crowd behaviour is that the close proximity of crowd members could be obtained by having low repulsion potential values so that crowd members are able to be close together. However, we argue that basing proximity on low repulsion cannot simulate psychological crowd behaviour, as this does not capture how crowd members attempted to remain together throughout the scenario. A second argument could be that if a modeller knows that psychological crowds move more slowly, one could set a slower speed for the entire crowd. This, however, would not capture how speed was reduced due to the maintenance of close proximity. While a model with reduced speed may be able to simulate the slower movement of the psychological crowd, this would not capture the close proximity that caused the slower speed and therefore would not provide an accurate simulation of the overall behaviour. To ascertain whether a self-categorisation parameter was needed to simulate psychological crowd behaviour, we used the physical model to determine whether the lower tessellation areas and reduced speed in the psychological crowd i) could be achieved using low repulsion potentials, and ii) whether there was a relationship between tessellation areas and speed walked.

(b) Psychological crowd

The psychological crowd model was tested using the maximum walking speed that best replicated the physical crowd behaviour. To determine how the attraction potentials between ingroup members affected the mean tessellation areas, speed, and distance, different attraction potentials are simulated based on the same repulsion distribution and heights in the physical crowd (from 0.5 metres to two in increments of 0.5 metres). Finally, we compare the attraction parameters to determine which values produced the best simulation of the tessellations areas, speed, and distance of the real psychological crowd.

m all simulations, Tables 8, 9, and 10 show the mean distance, speed, and tessellations areas respectively for each maximum walking speed and repulsion parameter variation based on five simulations of each version, and Figure 19 provides a visual indication of these trends.

When analysing the best simulation of the physical crowd, Kolmogorov-Smirnov tests showed that the mean tessellation areas, speed, and distance of the simulation were significantly non-normal (tessellation areas, $D(198) = .281$, $p < .001$; speed, $D(198) = .163$, $p < .001$; distance, $D(198) = .148$, $p < .001$); therefore non-parametric tests were used to compare behaviour. A Kruskal-Wallis test found that there was a non-significant difference between the tessellation areas of the agents in the simulation (*Mean rank* = 124.50) and the tessellation areas of the pedestrians in the footage (*Mean rank* = 116.68), $H(1) = 0.491$, $p = .483$, $r = -.04$. However, there was a significant difference in the speed walked by the agents in the simulation (*Mean rank* = 141.50) and the pedestrians in the footage (*Mean rank* = 105.50), $H(1) = 19.03$, $p < .001$, $r = -.27$. There was also a significant difference between the distance walked by the agents in the simulation (*Mean rank* = 165.50), and the pedestrians in the footage (*Mean rank* = 33.50), $H(1) = 150.12$, $p < .001$, $r = .75$. The significant differences in speed and proximity are unpacked in the discussion section, but we take this to be the best replication of the behavioural data from the footage of the physical crowd given the non-significant difference between tessellation areas, very similar mean speeds, and that all other versions of the simulation had greater differences.

Simulation results

(a) Physical crowd simulation

The best simulation of the physical crowd

The simulation which achieved the most similar behaviour to the pedestrians in the physical crowd footage was when maximum walking speed was set to 1.1 with the repulsion distribution of 0.5 metres and height of 1 metre. Table 2 shows a comparison of the means and standard deviations for speed, distance, and proximity, for the real crowd behaviour and the best simulation, and Figure 12 provides snapshots of both crowds. To demonstrate the data from all simulations, Tables 8, 9, and 10 show the mean distance, speed, and tessellations areas respectively for each maximum walking speed and repulsion parameter variation based on five simulations of each version, and Figure 19 provides a visual indication of these trends.

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Table 7

The distance, speed, and tessellation areas of the physical crowd in the behavioural data and the best version of the simulation

Physical crowd											
Distance walked (metres)				Speed (metres per second)				Proximity (cm^2)			
Data		Simulation		Data		Simulation		Data		Simulation	
M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
7.80	0.15	11.59	1.21	1.10	0.13	1.10	0.00	20506.39	6404.64	20395.90	415.84

(a) (b)

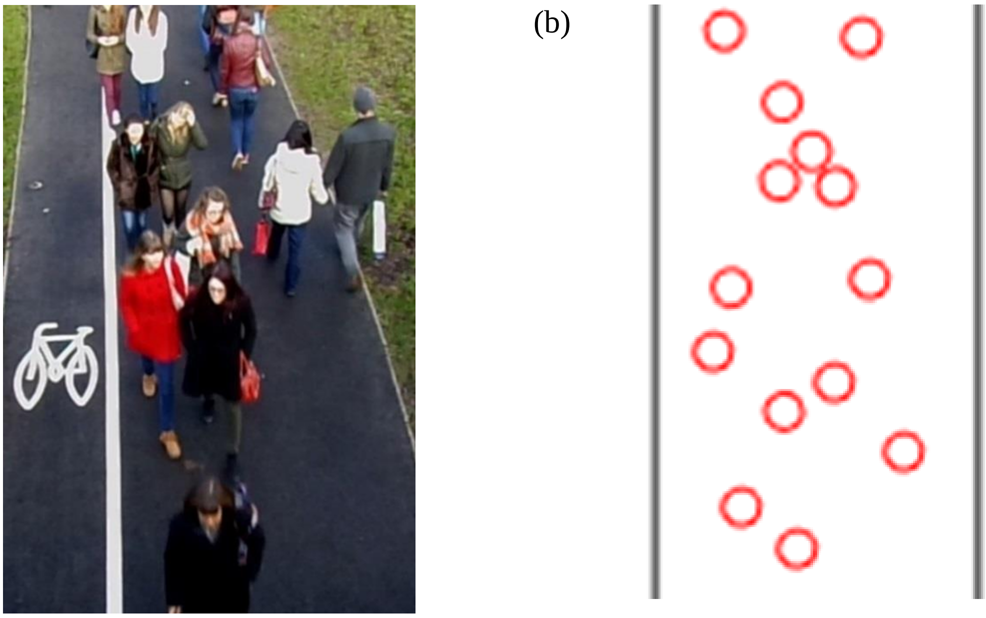


Figure 18. Snapshots of the physical crowds, denoting (a) the pedestrians in the physical crowd footage, and (b) excerpt from the physical crowd simulation where data was recorded. Red circles indicate agents, and the black lines represent the width of the path.

Table 8

Distance walked by agents for each variation of the repulsion parameters

	Distance (metres)									
	Maximum speed allocation									
	0.5		0.8		1.1		1.4		1.7	
Repulsion	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
0.5, 0.5	10.29	3.33	11.64	1.37	11.76	1.35	12.18	1.46	12.14	1.56
0.5, 1	11.28	2.67	11.52	1.24	11.76	1.31	11.91	1.54	12.59	1.81
0.5, 1.5	10.93	3.14	11.67	1.35	12.13	1.51	11.75	1.29	11.92	1.43
0.5, 2	10.51	3.47	12.13	1.75	12.31	1.55	12.01	1.37	11.89	1.49
1, 0.5	10.71	3.63	12.58	1.96	12.71	1.80	12.89	1.76	12.98	1.89
1, 1	11.11	3.73	12.80	1.74	12.83	1.79	12.70	1.89	13.21	1.77
1, 1.5	10.84	6.68	12.54	2.55	13.14	1.72	13.09	1.81	12.89	1.75
1, 2	10.36	3.90	12.87	1.89	12.84	1.59	13.08	1.89	12.81	1.95
1.5, 0.5	10.31	2.60	12.04	1.68	11.84	1.59	11.88	1.79	11.94	1.67
1.5, 1	10.90	2.83	11.99	1.54	11.88	1.55	11.96	1.49	11.84	1.45
1.5, 1.5	10.76	2.86	11.80	1.38	11.99	1.57	11.99	1.56	11.96	1.48
1.5, 2	10.24	2.86	11.86	1.43	11.95	1.51	11.89	1.33	11.88	1.34
2, 0.5	9.99	2.10	11.15	2.36	11.87	2.74	11.82	1.4	12.20	3.15
2, 1	9.61	2.52	11.10	1.71	11.38	1.76	11.57	1.97	11.31	1.72
2, 1.5	10.01	2.66	11.55	1.31	11.57	1.32	11.43	1.49	11.74	1.61
2, 2	10.23	2.71	11.43	1.54	11.62	1.75	11.98	1.63	11.74	1.61

Table 9

Speed walked by agents for each variation of the repulsion parameters

	Speed (metres per second)									
	Maximum speed allocation									
	0.5		0.8		1.1		1.4		1.7	
Repulsion	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
0.5	0.50	0.00	0.50	0.00	0.50	0.00	0.50	0.00	0.50	0.00
0.8	0.80	0.00	0.80	0.00	0.80	0.00	0.80	0.00	0.80	0.00
1.1	1.10	0.00	1.10	0.00	1.10	0.00	1.10	0.00	1.10	0.00
1.4	1.40	0.00	1.40	0.00	1.40	0.00	1.40	0.00	1.40	0.00
1.7	1.70	0.00	1.70	0.00	1.70	0.00	1.70	0.00	1.70	0.00

Figure 19. The mean speed, mean distance, and mean tessellation areas for each variation of repulsion distribution and height.

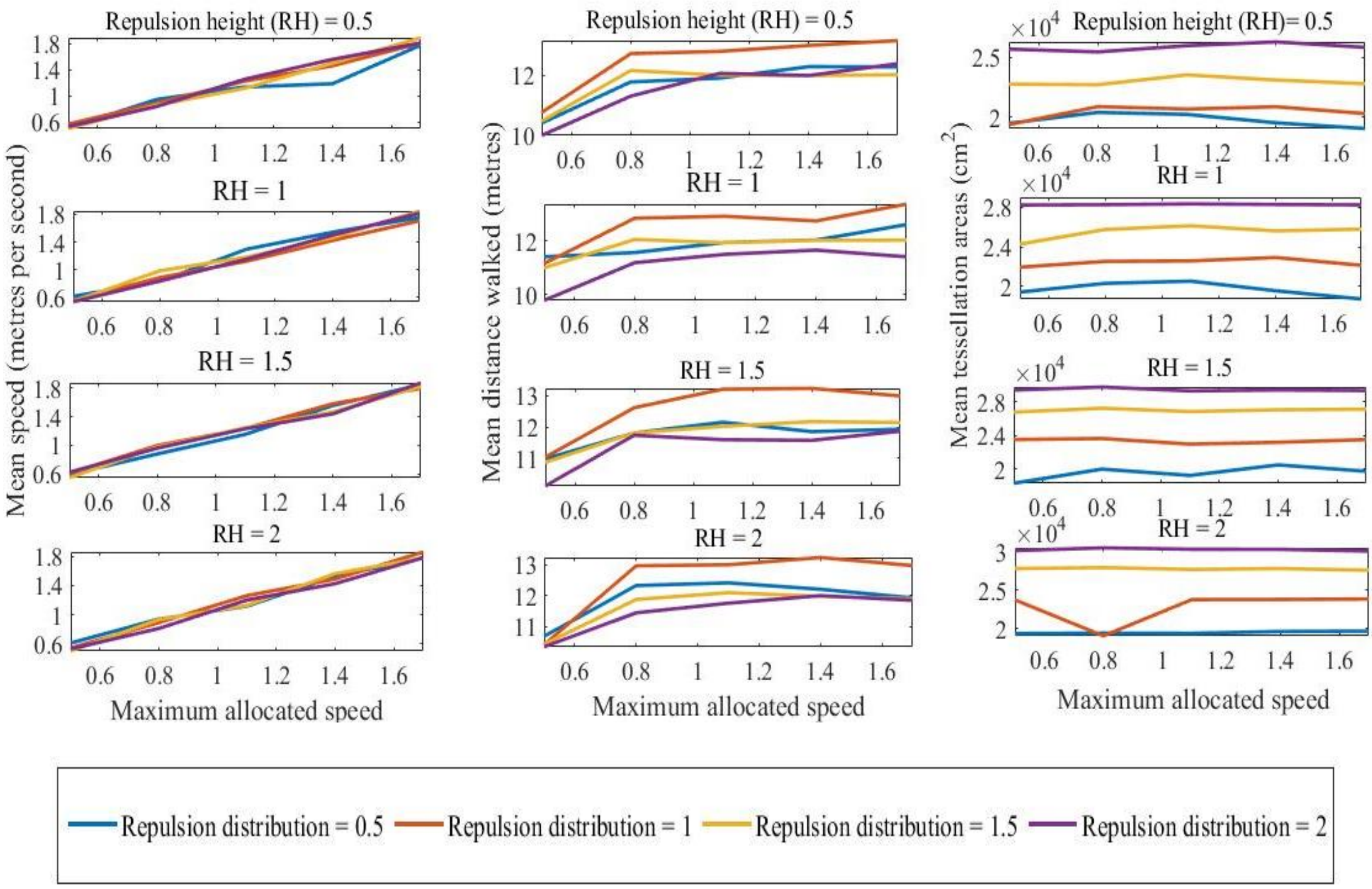


Table 10

Tessellation areas of agents for each variation of the repulsion parameters

	Tessellation areas (cm^2)									
	0.5		0.8		1.1		1.4		1.7	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
0.5, 0.5	19474.38	422.70	20392.82	310.35	20223.03	385.40	19515.51	206.96	19034.29	319.17
0.5, 1	19436.93	441.23	20314.60	328.16	20538.06	621.76	19567.24	984.09	18735.10	900.82
0.5, 1.5	18308.18	414.55	19991.68	396.03	19239.27	460.74	20494.78	213.01	19733.99	395.41
0.5, 2	19363.15	920.91	19417.11	289.18	19388.83	468.44	19634.03	733.96	19683.18	348.38
1, 0.5	19363.15	920.91	20872.26	453.21	20668.52	630.45	20864.93	595.28	20294.77	335.41
1, 1	21947.32	551.65	22534.74	298.19	22581.33	492.00	22920.59	274.82	22137.83	261.17
1, 1.5	23512.68	968.06	23636.57	503.05	22968.89	626.06	23188.17	337.49	23509.26	465.61
1, 2	23741.41	1009.22	19060.85	9447.62	23779.20	537.00	23799.44	459.60	23857.59	358.83
1.5, 0.5	22766.57	265.01	22714.33	439.84	23541.64	66.21	23109.61	239.51	22798.53	224.57
1.5, 1	24279.42	2499.84	25752.60	439.84	26127.18	228.12	25609.48	244.01	25782.86	425.65
1.5, 1.5	26779.20	362.65	27242.25	121.28	26843.55	80.54	27059.96	285.56	27127.41	74.65
1.5, 2	27818.35	275.66	27945.21	708.03	27708.61	176.26	27820.36	120.72	27608.76	557.87
2, 0.5	25708.19	556.64	25472.77	165.35	25995.64	144.64	26310.51	135.12	25855.10	210.49
2, 1	28216.43	556.64	28253.25	348.98	28332.94	311.99	28275.10	195.64	28233.28	290.89
2, 1.5	29401.86	288.97	29768.24	281.05	29304.50	158.36	29416.75	121.37	29349.50	293.77
2, 2	30161.39	137.60	30510.94	57.97	30332.96	62.63	30324.31	58.72	30092.85	48.83

Simulating the psychological crowd with a physical crowd model

To determine whether the low tessellation areas and related reduced walking speed of the psychological crowd could be obtained by simply allocating agents low repulsion potentials, the results of physical crowd simulation that produced the lowest tessellation areas were compared to the footage of the psychological crowd behaviour. The physical crowd simulation that produced the lowest tessellation areas (M = 18308.18) were when the maximum walking speed was set to 0.5 with repulsion distribution of 0.5 metres and height of 1.5 metres. A Kruskal-Wallis test showed that the tessellation areas produced by this simulation (*Mean rank* = 468.76) were still significantly larger than the tessellation areas of the real psychological crowd (*Mean rank* = 228.20), $H(1) = 245.31$, $p < .001$, $r = .34$. Moreover, the agents in the simulation walked significantly faster (*Mean rank*= 93.00) than the pedestrians in the psychological crowd (*Mean rank* = 213.50), $H(1) = 231.42$, $p < .001$, $r = .98$. This suggests that low repulsion parameters were not sufficient to replicate the tessellation areas of the psychological crowd, or how close proximity reduced walking speed.

To ascertain whether the physical crowd model could simulate how pedestrians walking in close proximity reduced speed, we examined the relationship between allocated maximum walking speed and tessellation areas across all simulations (taken as the tessellation areas across all repulsion potential variations for each speed). Jonckheere's test revealed that the trend was non-significant, J = 781,848,584.00, $z = .923$, $p = .356$, $r = .01$, showing that the tessellations areas did not change across the different speeds. However, a Kruskal-Wallis test showed a significant difference in tessellation areas between allocated maximum speeds, $H(4) = 59.65$, $p < .001$. Pairwise comparisons for each allocated maximum speed with adjusted p-values and r-values are shown in Table 11. Overall, this indicated that there is some difference between tessellation areas for particular walking speeds, but there is no overall significant trend. This supports our hypothesis that the physical crowd model was not sufficient to simulate how reduced speed was a function of close proximity in the psychological crowd.

Table 11

Pairwise comparisons of maximum allocated speeds, with significant differences in bold

Maximum walking speeds	Adjusted *p*-values	*r*-values
0.5 and 0.8	**.001**	-.04
0.5 and 1.1	**.017**	-.02
0.5 and 1.4	**.001**	-.04
0.5 and 1.7	1.00	.04
0.8 and 1.1	.401	.01
0.8 and 1.4	1.00	-.01
0.8 and 1.7	**.001**	.03
1.1 and 1.4	**.023**	-.02
1.1 and 1.7	.109	.02
1.4 and 1.7	**.001**	.04

(b) Psychological crowd simulation

Comparison of speed, distance, and tessellation area to the psychological crowd

The simulation that produced the most similar behaviour to the behaviour of the real psychological crowd was when attraction distribution was set to 1 metre radius around the agent, with an attraction height of 2 (see Table 12 for a comparison of the means for distance walked, speed, and tessellation areas of the real psychological crowd and the simulated version, and Figure 20 for snapshots of the real crowd and the simulation). The effect of attraction distributions and heights on mean speed, distance, and tessellation areas are shown in Table 13 and Figure 21 (this is based on three simulations of each version).

Kolmogorov-Smirnov tests revealed that all variables were significantly non-normally distributed: distance, $D(198) = .107$, $p < .001$; speed, $D(198) = .148$, $p < .001$, and tessellation areas, $D(198) = .107$, $p < .001$. A Kruskal-Wallis test demonstrated that there was a non-significant difference between the tessellation areas of the agents in the simulation (*Mean rank* = 328.17) and the tessellation areas of the pedestrians in the real psychological crowd (*Mean rank* = 299.17), $H(1) = 3.576$, $p = .059$, $r = .08$, suggesting that attraction potentials were able to replicate the maintenance of close proximity between ingroup members. However, the agents in the simulation walked a significantly faster (*Mean rank* = 179.27) than the pedestrians in the psychological crowd (*Mean rank* = 108.09), H(1) = 45.272, $p < .001$, $r = .38$, and the agents in the simulation walked significantly further (*Mean rank* = 188.45) than the pedestrians in the real crowd (*Mean rank* = 91.41), $H(1) = 84.038$, $p < .001$, $r = .52$. The significant differences in speed and distance are addressed in the discussion section.

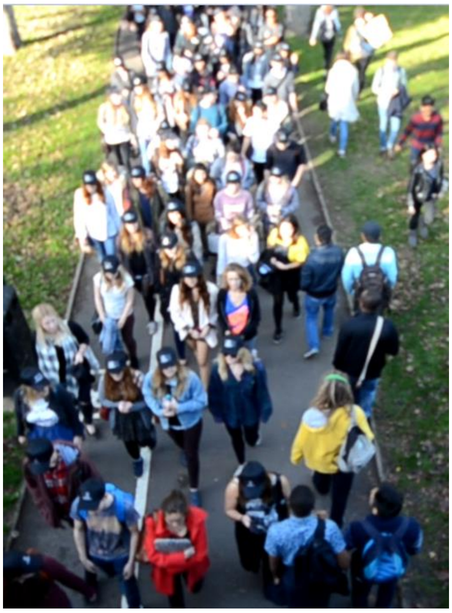
Despite the significant differences in speed and distance for this particular simulation, Jonckheere's test was used to determine whether increased attraction to ingroup members affected speed and distance across all simulations. It revealed that attraction levels did significantly affect speed and distance: as attraction increased, the speed of agents decreased, $J = 1{,}331{,}926.00$, $z = -32.287$, $p < .001$, $r = -0.6$, and distance walked increased, $J = 2{,}983{,}249.00$, $z = 36.436$, $p < .001$, $r = .07$. Overall, this suggests that attraction to ingroup members was able to replicate the decreased speed and increased distance walked that occurred in the psychological crowd.

Table 12

The mean distance, speed, and tessellation areas of psychological crowds in the behavioural data and the best version of the simulation

Psychological crowd											
Distance walked (metres)				Speed (metres per second)				Proximity (cm^2)			
Data		Simulation		Data		Simulation		Data		Simulation	
M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
14.13	0.68	19.69	3.27	0.89	0.05	0.95	0.05	10383.29	5503.68	10141.37	1087.82

(a)



(b)

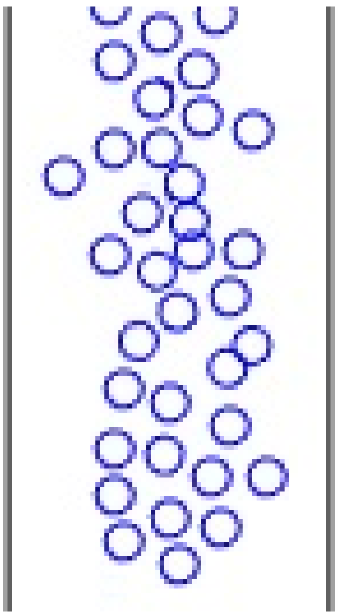


Figure 20: Snapshots of the psychological crowd condition, denoting (a) the pedestrians in the psychological crowd scenario, and (b) the simulated version of scenario.

Table 13

The mean distance walked, speed, and tessellation areas for each variation of the attraction parameters

Psychological crowd						
Attraction (distribution, height)	Distance walked (metres)		Speed (metres per second)		Tessellation areas (cm^2)	
	M	*SD*	*M*	*SD*	*M*	*SD*
0.5, 0.5	10.98	1.22	1.10	0.00	20745.79	466.55
0.5, 1	11.25	1.47	1.10	0.00	19502.62	401.75
0.5, 1.5	10.88	1.24	1.09	0.00	20879.92	453.39
0.5, 2	12.49	2.03	1.10	0.00	24161.77	661.88
1, 0.5	13.25	1.79	1.10	0.01	15537.70	240.72
1, 1	12.22	3.43	1.09	0.04	13103.50	635.36
1, 1.5	15.99	2.99	1.07	0.05	13622.66	947.36
1, 2	19.69	3.27	0.95	0.05	10141.37	1087.82
1.5, 0.5	14.28	2.19	1.09	0.03	13651.23	47.37
1.5, 1	12.91	1.92	1.10	0.00	24011.70	596.13
1.5, 1.5	21.36	8.78	0.89	0.07	8743.26	330.81
1.5, 2	13.32	1.84	1.10	0.01	23528.61	228.26
2, 0.5	17.61	3.56	1.05	0.06	10635.42	459.41
2, 1	22.42	3.02	0.81	0.12	5400.08	1557.01
2, 1.5	20.97	1.02	0.91	0.18	12968.05	1027.28
2, 2	26.52	4.08	0.85	0.19	8515.87	1233.11

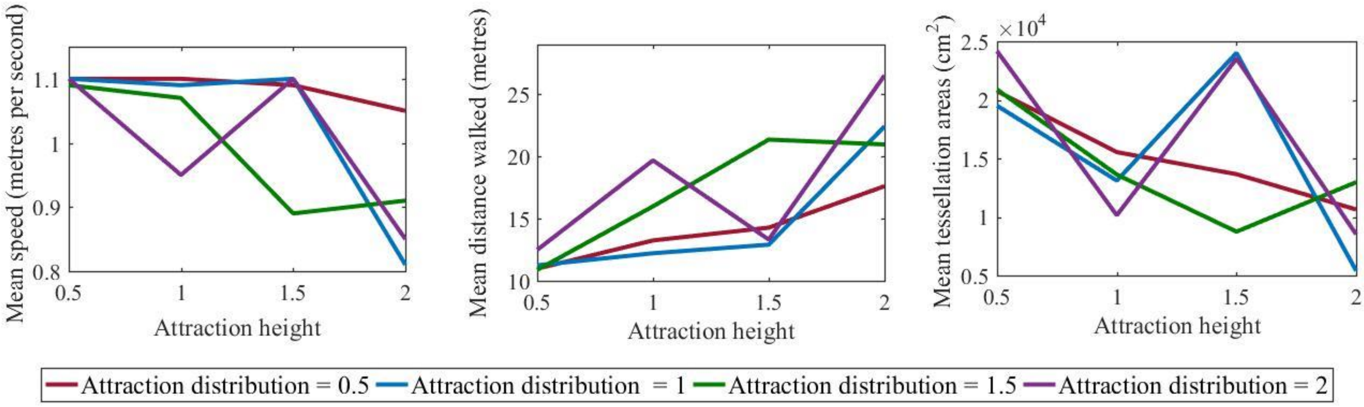


Figure 21: The mean speed, mean distance, and mean tessellation areas for each variation of repulsion distribution and height.

Discussion

This paper presents the first attempt to simulate the collective self-organisation of psychological crowds using aspects of SCT based on behaviour data. We addressed the key differences between the movement of physical and psychological crowds, and demonstrated that a self-categorisation parameter was needed to replicate the close proximity maintained by the psychological crowd to move together as a large group. First, we showed that our pedestrian movement model could replicate the proximity between members of a physical crowd using repulsion potentials. Second, we showed that allocating low repulsion potentials and a slow maximum walking sleep in the physical crowd were not sufficient to simulation the behaviour of the psychological crowd. Although allocating low repulsion potentials resulted in closer proximity between crowd members (although still significantly further than the proximity of the psychological crowd), and setting a slow maximum walking speed achieved the similar slow speed to the psychological crowd, they could not simultaneously replicate how the speed of the psychological crowd was reduced by ingroup members maintaining close proximity. Finally, we presented a model of psychological crowd behaviour validated against the proximity found in the behavioural data. We demonstrated that close proximity between ingroup members could be maintained by implementing a self-categorisation parameter based on aspects of SCT that provided agents with a shared social identity and allowed them to coordinate their behaviour according to attraction towards ingroup members.

Our simulations of psychological crowd behaviour could not replicate the walking speed and distance of the real psychological crowd, but we demonstrate that the maintenance of close proximity resulted in the trend of decreased speed and increased distance found in the psychological crowd behaviour. Thus, our computer model progresses from previous models of pedestrian crowd behaviour which assess small groups in crowd flow (e.g. Moussaïd et al., 2010; Moussaïd et al., 2011), as we demonstrate that attraction potentials can be used to simulate the close proximity of an entire crowd moving together as a group. Crucially, our model incorporates self-categorisation to simulate the attempt of large psychological groups with a shared social identity to remain together.

There are some potential limitations to this model and avenues for future research. The model is validated against the behavioural data from footage obtained by Templeton et al. (in preparation). In those studies, a naturally occurring physical crowd was filmed to obtain natural crowd behaviour and compare it to when the pedestrians were primed to share a social identity. This method was chosen to ensure that the behaviour of the crowd was due to categorising one another as ingroup members, in order to compare behaviour between when participants shared a salient social identity and when they did not. However, this artificially created psychological crowd may lack ecological validity and generalisability to other psychological crowds. Future research could examine the model against naturally occurring psychological crowds at events where crowds have been found to share social identities, such as protests and music festivals (Neville & Reicher, 2011; Novelli, et al., 2013), football fans (Stott et al., 2001), religious pilgrimages (Alnabulsi & Drury, 2014), and emergency evacuations (Cocking & Drury, 2014; Drury et al., 2009a, 2009b; Drury et al., 2015). The model allows users to vary group sizes and have multiple groups with different social identities; the model could also be tested against behavioural data of both physical and psychological crowds of different sizes, densities, and group numbers to determine whether this model is applicable to different crowd sizes and group compositions.

Another limitation of the model is that there were significant differences between the speed and distances walked in the real crowds and the simulated crowds that were chosen as the best fit. This could be an artefact of the model; agents will walk the maximum speed possible if they are not obstructed by other agents. In the physical crowd simulations, almost every agent walks the maximum speed possible because they are not obstructed by others, but this effect is not found in the psychological crowd where speed is reduced due to attraction to ingroup members even when agents are not obstructed. Overall, this trend is consistent with the behavioural data from the real crowds, and the mean speeds of the real and simulated physical crowd are identical. The differences appears to arise from the distribution of speeds in the real crowd compared to the identical speeds of all agents in the physical crowd.

The longer distance walked in both the physical and psychological crowd simulations could also be an artefact of the number of positions allocated to the step circle, which although increases the number of potential directions of movement, in our model it does not allow for direct forward stepping and thus increases the distance as the agents progress forward due to slight zig-zagging. Notably, speed is calculated using distance, so if the distance is increased then so is the overall speed which could explain the faster speed of agents in the simulations. Future research could increase the number of potential directions on the step-circle to determine the optimal amount for fluid movement while maintaining low computational load. Additional parameters may also be needed to influence steering in the simulation, for example by increasing the repulsion potentials of obstacles on the floor-field (such as paths or walls), or altering attraction potentials of targets. Moreover, we echo Seitz and Köster (2012) who suggest that the circular shapes used in the OSM could be replaced with ellipses to better model the human body. Ellipses would more accurately simulate how agents manoeuvre around each other, which could be particularly importantly for modelling heavily dense crowds such as at bottlenecks, crowd crushes, and the effect of shockwaves.

Crowd modelling is a useful tool for planning for the safety of mass events, particularly for predicting and monitoring crowd behaviour. We provide evidence that to simulate psychological crowd events accurately, models should include the shared identification between group members and attraction towards ingroup members. Equally important, however, is understanding the psychology of the crowd that is being planned for. Our model can replicate the close proximity maintained amongst ingroup members, but social groups also have a set of social norms associated with them which guide behaviour, leading different crowds to behave in distinctive ways. For example, research by Stott et al. (2001) demonstrates that fans of one football team had a social norm of acting in a disorderly way, while fans of another team had a social norm of non-violence causing them to behave in different ways. Future models of psychological crowd behaviour could build on our psychological crowd movement model to include social norms of particular crowds, such as the helping behaviour implemented in von Sivers et al. (2016). Models which attempt to simulate social norms, however, should be conscious of the potential to over-fit a model to one particular crowd and limit its generalisability to other crowd events.

Research from social psychology has shown that understanding the crowd can be crucial to maintaining the safety of crowd events, such as stopping potentially dangerous behaviour and crushes at a music event (Drury et al., 2015), and in mass decontaminations where understanding of the needs of the crowd and importance of social identities increased people’s willingness to respond to safety professionals (Carter, Drury, Amlôt, Rubin and Williams, 2014). We provide a crowd model which makes the first steps towards accurately simulating psychological crowd behaviour, but we argue that this should be combined with a broader understanding of social norms to ensure the maximum chance of safety at mass events.

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Appendix 1: Questionnaire

Walk This Way

University of Sussex

Thank you for agreeing to take part in this study. Please answer the following questions to the best of your ability.

Section 1

Which group are you a member of? ____

Please answer the following questions based on your feelings towards **your** group. Please answer from 1 (not at all) to 7 (very much).

	(1: Not at all)						(7: Very much)
I feel a bond with the people in this group	1	2	3	4	5	6	7
I feel an affinity with this group	1	2	3	4	5	6	7
I feel committed to this group	1	2	3	4	5	6	7

Section 2

Who are the other group? ____

Please answer the following questions based on your feelings towards **the other** group. Please answer from 1 (not at all) to 7 (very much).

	(1: Not at all)						(7: Very much)
I feel a bond with the people in this group	1	2	3	4	5	6	7
I feel an affinity with this group	1	2	3	4	5	6	7
I feel committed to this group	1	2	3	4	5	6	7

Thank you for answering these questions. Please return this questionnaire to the researcher and await further instruction.