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Emotion contagion in agent-based simulations of crowds: a systematic review

E. S. van Haeringen[1] · C. Gerritsen[1] · K. V. Hindriks[1]

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Abstract
Emotions are known to spread among people, a process known as emotion contagion. Both positive and negative emotions are believed to be contagious, but the mass spread of negative emotions has attracted the most attention due to its danger to society. The use of agent-based techniques to simulate emotion contagion in crowds has grown over the last decade and a range of contagion mechanisms and applications have been considered. With this review we aim to give a comprehensive overview of agent-based methods to implement emotion contagion in crowd simulations. We took a systematic approach and collected studies from Web of Science, Scopus, IEEE and ACM that propose agent-based models that include a process of emotion contagion in crowds. We classify the models in three categories based on the mechanism of emotion contagion and analyse the contagion mechanism, application and findings of the studies. Additionally, a broad overview is given of other agent characteristics that are commonly considered in the models. We conclude that there are fundamental theoretical differences among the mechanisms of emotion contagion that reflect a difference in view on the contagion process and its application, although findings from comparative studies are inconclusive. Further, while large theoretical progress has been made in recent years, empirical evaluation of the proposed models is lagging behind due to the complexity of reliably measuring emotions and context in large groups. We make several suggestions on a way forward regarding validation to eventually justify the application of models of emotion contagion in society.

Keywords Emotion contagion · Crowd simulation · Agent-based · Collective emotion · Computational modelling

1 Introduction

Emotion contagion, the flow of affect among people, drives the formation of collective emotion and thereby impacts group dynamics. While both positive and negative emotions have been suggested to be contagious, research involving crowds has largely focussed on the contagion of negative emotions in scenarios like evacuations, riots and failure of public

E. S. van Haeringen
e.s.van.haeringen@vu.nl

[1] Faculty of Science, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

services. In these events, emotion spirals are thought to trigger collective behaviour that is irrational and difficult to manage, and may lead to dire consequences.

A recent example is the mass-panic that broke out during a burial procession that drew a large crowd in Teheran, Iran [1, 2]. The procession travelled through narrow streets, where some of the side streets had been closed when they met another group that was heading in the opposite direction. The extreme fear that spread quickly through the crowd resulted in a large number of casualties and injured as they were trampled or suffocated by the fleeing crowd. Other recent examples are the riots that took place in several cities in the United States following nationwide protests against institutional racism. While in most protesting crowds the atmosphere was emotional yet remained peaceful and cooperative, in some crowds collective aggression flared which resulted in at least a dozen deaths and hundreds that were injured among civilians and members of law enforcement, as well as extensive property damage [3, 4].

The rapid escalation and severe consequences of such events emphasize the challenge governments, civil engineers, event planners and security staff face in managing emotional crowds. Moreover, factors such as the increasing urbanisation [5] and growing access to internet and social media [6, 7] may facilitate the organisation of (spontaneous) large-scale events and the fast spread of sentiments [8–11]. Hence, in recent years calls have been echoed to improve the understanding of crowd dynamics, and to develop realistic models and tools that may be used in planning and management decisions and in training.

For this purpose several data-driven approaches have been developed such as sentiment, movement and smartphone tracking [12–15], as well as a variety of mathematical and computational modelling approaches. In the present review we are particularly interested in simulations of emotion contagion in crowds that use agent-based models. This bottom-up approach is suitable because it acknowledges the heterogenic nature of the crowd, which is known to affect the contagion process [16]. This area of research draws upon the fields of social and neuro science to study emergent collective behaviour by considering individual psychological and cognitive aspects of crowd members at a microscopic level. This includes elements such as the emotional state, personality, mood, knowledge, goals and social relationships of agents to improve the resemblance to real crowds.

With this systematic review we aim to give a comprehensive overview of agent-based methods to simulate the spread of emotions due to social interaction in human crowds. While the number of agent-based models that consider emotion contagion has grown rapidly in recent years, a clear synthesis is lacking on the wide range of contagion mechanisms, simulated scenarios and individual traits that have been considered. And, while there are some surveys that explore literature that overlaps with the present paper, these focus on different aspects such as crowd simulation in general [17, 18], simulating emotions and behaviour in emergencies [19] and agent-based simulation of emotion [20]. Therefore, a systematic literature review dedicated to agent-based models of emotion contagion is important to establish a common baseline and aid further research. We formulated the following research questions with the aim of producing a structured overview and providing directions for future study:

1. How can the identified agent-based contagion mechanisms be structured into categories?
2. What are the theoretical consequences of the fundamental differences among the identified categories for the applications, performance and limitations of the contagion mechanisms?
3. What are the current gaps in research involving agent-based emotion contagion?

This paper is organised in five sections. In Sect. 2 the theoretical background of emotion contagion and crowd modelling is discussed. Section 3 contains the methodology. In Sect. 4, first the results of the literature collection and selection process are given. Then a brief overview is given of other characteristics of the agent that are commonly considered in the selected studies, followed by an analysis of the identified contagion mechanisms and the findings of the selected studies. Finally, in Sect. 5 the second and third research questions are answered by discussing the differences among the contagion mechanisms and identifying several areas for future research.

2 Theoretical framework

2.1 Simulating emotional crowds

The research discussed in the present pasper combines elements from two fields of study, namely computational modelling of the emotional and cognitive states of a person, and modelling behaviour and interactions of the multi-agent system that makes up a crowd.

A crowd is an example of a complex system in which the interactions between individual entities, in this case the behaviour of people, results in emergent patterns at the level of the group. These patterns cannot merely be explained as the sum of the individual parts, yet are affected by individual properties. A large body of research has focussed on developing models and simulation tools of crowd dynamics to both analyse and predict crowd behaviour with the aim of improving management and design decisions regarding safety in the crowd [17, 18]. The affective component, the focus of the current paper, is one of many aspects that is considered to improve the realism of the simulated crowd.

What is labelled as a crowd differs among studies, ranging from an intentional gathering for an organised event, to people sharing an office, to random clusters of pedestrians. In the present paper we define a crowd as a large gathering of people in close spatio-temporal proximity, who do not have an immediate relationship with all other people that are present. This general definition for instance covers both intentional gatherings for an organised event as well as random clusters of pedestrians if the gathering is sufficiently large, while a team of co-workers sharing an office are not considered a crowd. Note that the qualifier large is a relative term that is left open for interpretation. What is considered a large crowd in one scenario may be a relatively small number of people in another. The smallest number of agents simulated by a study included in the present review [21] was ten agents because the authors state that the agents start out unfamiliar to each other while they are in close proximity.

As this review focusses on emotion contagion, specifying the used definition of emotion is desirable, especially since the definitions of terms related to emotion vary among applications and scientific disciplines, and may be different from the everyday intuitive meaning of these terms. However, since not all examined studies share a single definition of emotion, we refer to the individual studies in this regard.

Lin et al. [22] present an overview of computational models of emotion and cognition. The authors find that these computational models differ from the models used in psychology and cognitive science in the level of detail of the processes and data that are involved in order to implement them on a computer, particularly lacking in the intimate interplay between emotion and cognition. The authors however do not present a clear verdict on the practical acceptability of these computational models. According to Lin et al. most of the computational models involve a form of appraisal theory, in which the judgement by a person of perceived instances such as events, objects or situations in conjunction with the beliefs, desires and intentions of these individuals give rise to emotions in a predictable manner. Appraisal theories differ in the variables (dimensions) that are used to form appraisals and the way they are mapped to generate emotions, yet generally they share the concept of valence (positivity of an event) and arousal (intensity of the feeling).

An appraisal model that is also applied in several studies discussed in the present paper is that of Ortony, Clore, and Collins, also referred to as the OCC model [23]. The OCC model defines 22 categorical emotions based on the appraisal variables valence, arousal, event desirability, action praiseworthiness, the likability of an entity, and whether the event was attributable to oneself or someone else. Dimensional theories of emotion generation are comparable to appraisal-based theories in that stimuli are mapped to emotional states. However instead of categorical states, the emotional state of an individual is represented by a point location in a multidimensional space with continuous axes. Well-known examples also found in studies discussed in the present paper are the circumflex theory [24] and the PAD dimensional theory [25]. However, many of the studies examined in the present review use simpler models of emotion, for example defining one categorical emotion like fear as a parameter of an agent, that directly affects its behaviour and the level of fear of other agents.

2.2 Emotion contagion

Emotion contagion is a social process wherein a person takes up emotion expressed by another person to some degree [26]. As this person also transmits its own emotional state, this can result in continuous feedback that is thought to contribute to convergence of emotion and behaviour in groups. One of the first and highly influential accounts of this phenomenon is that of Le Bon [27], who introduced the concept that emotional and cognitive states can be infectious, which is still widely reflected in current research [28, 29].

Since then, emotion contagion has extensively been studied in behavioural and social sciences at the level of the individual [28, 30] and the group [26]. Emotion contagion is believed to be a complex multilevel phenomenon [26], and may occur via at least three mechanisms that are not mutually exclusive [31]. The primary form of emotion contagion is based on automatic mimicry [30, 32]. In this process features of another person are reflexively imitated, such as facial expressions, speech profile, body posture, gestures and gaze direction [33]. These imitations occur spontaneously and often without the subject being consciously aware of this [34]. Further, mimicking emotional expressions of others is thought to affect one's own emotional state, an idea already proposed by Darwin [35]. In recent years embodiment frameworks, also called grounded cognition theories, have been popular to explain how higher-level processing of emotional information is grounded in perceptual, somatovisceral and motoric re-experiencing, together referred to as the embodiment of emotions [36, 37]. A second mechanism is that of category activation [38]. Here, an emotional expression triggers an emotion category that results in the activation of an emotion. Because this process does not depend on mimicking bodily expressions, this process has been suggested to be especially important in the contagion of other types of emotional expressions, like via text. The third mechanism operates via social appraisals [39]. In this mechanism the appraisals of others are used to steer one's own appraisal.

However, this level of detail about the bodily state of an agent or different forms of contagion are not included in any of the examined models of emotion contagion in this review.

With some notable exceptions like [40], the contagion process is commonly abstracted to the expression of emotional information by one agent in an undefined manner. This is followed by the perception and processing of this information to influence the emotional state of another agent, often without a specified modality and without changes in the bodily state (see Sect. 4.2).

3 Method

3.1 Approach

For the present review we have chosen a systematic approach to promote the reliability and transparency of the process. We followed the guidelines of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [41] for the collection and selection of literature as set out in the PRISMA 2020 checklist. We performed a review of the relevant literature in line with these guidelines but did not perform a meta-analysis, because most papers included in the review do not report results in a way that facilitates a comparison. Therefore, instead, our objective is to evaluate the emotion contagion mechanisms in two ways that are more suitable to the collected work. The first is by analysing the theoretical consequences and limitations of the different mechanisms to their performance and applications. The second is by reviewing the evidence from a handful of studies that directly compare mechanisms of emotion contagion, while keeping the other aspects of the simulated system equal. For the same reason, we applied an inclusive attitude towards selecting studies with respect to the quality. The full collection and selection process was conducted manually by one of the authors.

3.2 Inclusion criteria

We defined seven criteria that a study had to meet to be included in this review. The first four inclusion criteria are related to the form. A study was only included if 1) it is published in a journal, conference proceedings or dissertation, 2) published no earlier than 2011, 3) fully written in English and 4) was not part of an extended publication at a later date. The other three criteria concerned the content. A study had to 5) present an agent-based model that involves the contagion of emotion among agents, 6) with a clear explanation of the mechanism of emotion contagion and detailed methodology for the performed simulations and analysis. Also, the study had to 7) include at least one simulation of emotion contagion in a human crowd, contrary for example to pair-wise interactions, groups of animals or a virtual crowd such as the users of a social media platform (see Sect. 2.1 for our definition of a crowd).

3.3 Literature collection

We formulated two search queries: 1) "emotion* contagion" AND crowd AND (simulation OR model), and 2) "collective emotion*" AND crowd AND (simulation OR model). The star in emotion* can stand for any set of letters following the word, capturing variants like 'emotion', 'emotions', 'emotional'.

The final literature search was performed on August 31st 2021 in four databases: Scopus, Web of Science, IEEE and ACM as described in Table 1. We chose these databases

Table 1 Sources and search methods

Database	Method	Filters	Search date
Scopus	Title, abstract & keywords	Type = article or conference paper Publication date = 2011–2021	31-08-2021
Web of Science	Topic (Title, abstract & keywords)	Type = article, proceedings paper or early access Publication date = 2011–2021	31-08-2021
IEEE	Full text & metadata	Type = conferences or journals or early access articles Publication date = 2011–2021	31-08-2021
ACM (in Guide to Computing Literature)	Full text & metadata	Type = Proceedings, journals or other periodicals Publication date = 2011–2021	31–08-2021

because they offer research from a large collection of fields. This suits the diverse variety of scientific disciplines studying emotion contagion and crowd dynamics. We opted for a full text search in the two databases that provide this, IEEE and ACM, to further increase our coverage. Lastly, to lower the number of papers that had to be assessed, we applied filters for the type of paper and publication date in accordance with criteria 1 and 2.

3.4 Literature selection

The selection process was split in two phases. First a preselection was made by screening the metainformation of the study, specifically the publication type and date (criterium 1 and 2) and information about prior versions (criterium 4). Further the title and abstract (criterium 5) of each paper were examined, where studies were excluded that in an obvious way did not present an agent-based model or did not specify the spread or contagion of emotions among people.

The full-text was retrieved of all studies that were eligible for the second phase of selection. In the second phase the methods section and results of the remaining papers were read to confirm the paper proposed an agent-based model with a clearly explained mechanism of emotion contagion (criteria 5 and 6), and whether the study performed a simulation where emotions spread in a human crowd due to emotion contagion (criteria 7 and 8). Additionally, all sections of the study had to be written in English (criterium 3). A study was rejected if it failed to meet any of the inclusion criteria.

3.5 Analysis

The first research question of this review is how the identified models can be grouped based on their mechanism of emotion contagion in order to produce a structured overview. For this purpose, we propose three categories, called group statistic, epidemiological, dyadic relations (Fig. 1). The two features that delineate categories are 1) whether contagion occurs quantitatively or categorically and 2) whether the interactions are considered on a dyadic or group level. The group statistic category contains models where the emotion of an agent is affected quantitatively based on a local group statistic (like the average emotion). The epidemiological-based mechanisms model contagion as a categorical change in state of the receiver, shifting from a susceptible to an infected state. The dyadic relations category contains models that consider quantitative contagion at a dyadic level where individual properties of the sender and receiver (e.g. personality) and/or their connection (e.g. physical distance) determine the flow of emotion between them.

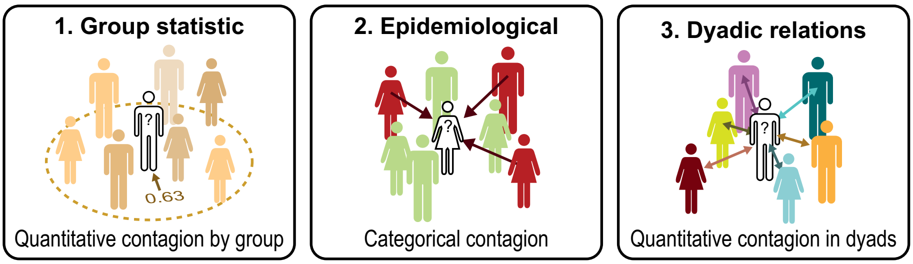


Fig. 1 Classification of agent-based mechanisms of emotion contagion

Per category, we show in detail the variation in mechanisms of contagion. Because we only focus on the emotion contagion aspect of the different models and aim to compare this, we have reformulated the relevant equations by using common symbols and structure. Additionally, we present a brief discussion on other features than the contagion mechanism that were common to the examined models. For this we collect the following data from each study: The nature and size of the scenario that was simulated, other features of the agents common to the models including the emotion, mood, decision, perception and navigation models that were used, as well as features that are stable sources of individual variation in the contagion process including personality, social relationships and culture.

For our second objective, to evaluate the application and performance of the models, we collect data on the application, the findings and how the model was validated. Additionally, we discuss the conclusions of several studies that directly compared the performance of various models. For the third objective, to identify gaps and make recommendations for future study, we draw upon our analysis of the first two objectives, as well as from the discussions in literature.

4 Results

4.1 Search results

The search process resulted in a total of 170 unique papers of which 136 were rejected based on our criteria (see Sect. 3.2), leaving 34 studies (20%) that were included in this review (see the tables in Sect. 4.3 for a list of the included studies). Figure 2 shows the details of the selection process per information source and in total. Note that there is both overlap in studies among the information sources as well as within the information sources if a study was found with both search queries. Most of the rejections were based on criterium 5 that required the study to present an agent-based model of emotion contagion. The publication date of the studies was limited from 2011 till 2021 as per criterium 2. Comparing the number of publications in the first half of Fig. 3 with those the second half, and considering 2021 was only partially included in the search, we conclude the research output involving agent-based models of emotion contagion in crowds has increased over the last decade.

4.2 Agent characteristics

While some studies focus solely on emotion contagion, most strive to simulate a specific scenario wherein emotion contagion is combined with other aspects of agents to produce agents that resemble the people in the intended scenario. In this section we aim to give a overview of other agent characteristics in the examined models that are frequently considered as shown Table 2. Below we describe briefly how these aspects typically relate to the process of emotion contagion.

4.2.1 Emotions and mood

The majority of the studies in the present review simulated the spread of a single categorical emotion (see Table 2). In most cases this was a negative emotion, particularly fear and anger. In many scenarios however, simulating only one categorical emotion is not sufficient

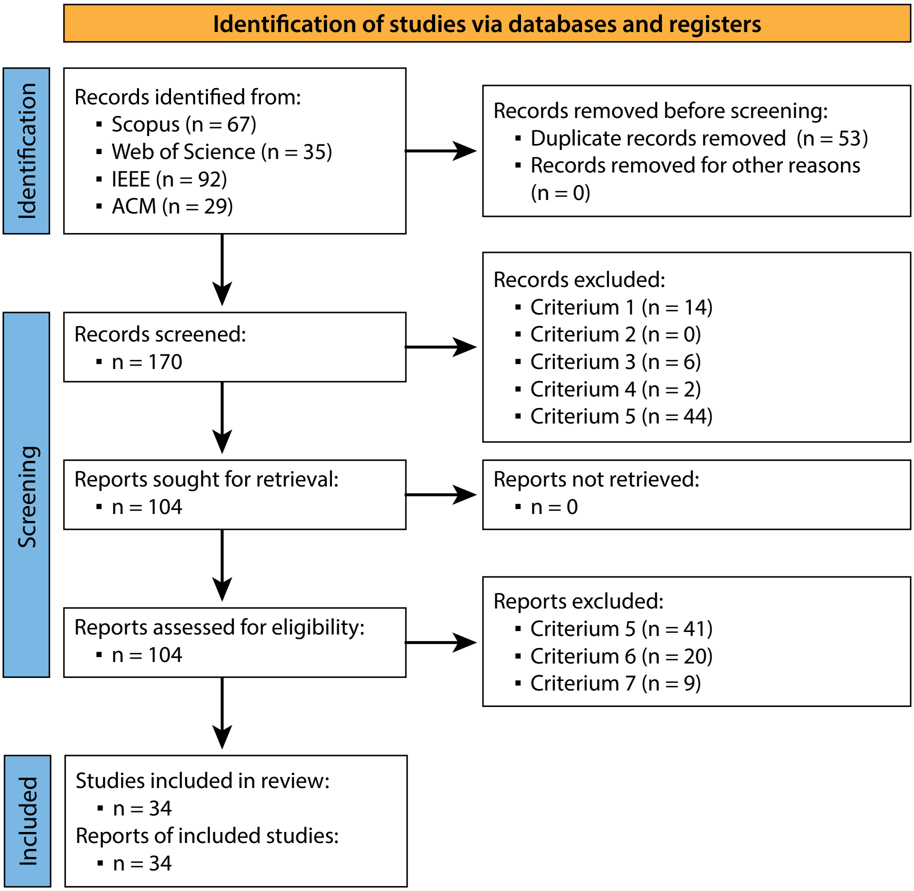
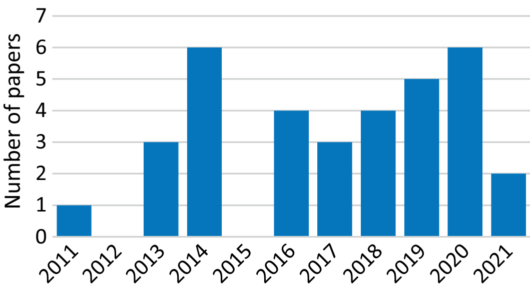


Fig. 2 PRISMA flow diagram [41] of the collection and selection process in the present study

Fig. 3 Publication year of selected studies



to describe the variety of emotional behaviour. Therefore, several studies have simulated the contagion of multiple categorical emotions, most commonly by implementing a form of the OCC (Ortony, Clore, Collins) model of emotions (see Sect. 2.2). Finally, there are a few studies that have considered continuous emotion, also known as Dimension theory. A well-known model of continuous emotion is the PAD (Pleasure-Arousal-Dominance)

Table 2 Common characteristics of included studies

Characteristic	Type	N	Studies
Emotion	Fear/panic	14	[46, 50, 49–51, 42, 60–63, 49, 77, 82, 79]
	Anger/grievance	5	[53, 67, 80, 64, 68]
	Multiple categorical emotions/OCC model	8	[40, 59, 69, 73, 75, 73–75]
	Positive, negative	4	[54, 65, 81, 76]
	Dimensional	2	[21, 78]
Mood	Dimensional	5	[40, 59, 69, 73, 78]
Perception	Range-based, no specific modality	24	[46, 58, 51–54, 58–63, 65–67, 73, 72–74, 54, 79–82]
	Visual field of view	3	[40, 68, 69]
	Multiple modalities	2	[50, 42]
Decision	Rule-based	13	[50, 42, 51, 63, 66, 79, 66–69, 54, 81, 72]
	BDI/cognitive model	9	[40, 46, 58, 49, 53, 75, 74–76]
	Game theory	2	[64, 65]
	Finite state machine	2	[77, 78]
	Scale-based model	1	[73]
	Neuro-fuzzy logic network	1	[80]
Navigation/steering	Cellular automaton/grid-based	7	[42, 65–67, 74, 65, 81]
	Particle-based (Social Force Model)	7	[62, 63, 80, 68, 59, 52, 54]
	Path planning	5	[60, 61, 79, 69, 70]
	RVO	5	[50, 58, 60, 61, 51]
	Unity	1	[40]
	OpenSteer	1	[46]
	BioCrowds	1	[72]
	Categorical directions	1	[49]

Table 2 (continued)

Characteristic	Type	N	Studies
Personality	OCEAN model (Big Five)	14	[40, 50–52, 59–63, 68–70, 70, 52]
	Susceptibility characteristic	15	[21, 58, 66, 49, 65–67, 80, 74–78, 78, 72]
	Expressivity characteristic	13	[58, 66, 65–67, 80, 74–78, 78, 72]
	Amplification characteristic	3	[49, 75, 72]
	Impulsiveness characteristic	1	[75]
Social relationships	Intimacy/confidence/trust	7	[21, 82, 80, 64, 59, 70, 74]
	Parent–child	3	[46, 77, 52]
	Leader–follower	4	[79, 80, 52, 74]
	Calming authority-civilian	5	[46, 62, 63, 79, 53]
	Policing authority-civilian	3	[40, 67, 65]
	Activist-civilian	1	[65]

model. It describes the emotional state of an agent as a location in a three-dimensional space and emotional change equals movement in this space. In the examined studies however the PAD model is more often used to simulate the mood of agents. Where emotions are defined as short-lived responses to specific triggers, the mood of a person is commonly defined as a generalized state over a longer period of time that is the result of a collection of inputs and is affected by the personality of an individual. The difference in duration between mood and emotions is assumed to dampen the emotional response of an agent if the triggered emotion differs from its mood.

4.2.2 Perception

A person in a crowd is not omniscient to all events that take place in the crowd. The viewing range is limited and sight can be blocked by others, objects or smoke. Sound on the other hand is not limited to an angle and can be drowned out by other sounds from all directions. If assumed that the contagion of emotions occurs through the expression and perception of emotive cues, then what is and is not perceived by an agent becomes an important aspect in the contagion process. As shown in Table 2, the majority of the models discussed in the present review simplify perception in the context of emotion contagion to a range-based area in which others may affect an agent. Several studies have considered specific modalities like a visual field of view and a unidirectional hearing range. While in most studies the perception determines which neighbours are considered in the contagion process, one recent study [42] also defined an impact of emotion contagion that depended on the perception domain the emotional information is received through, where they assumed visual information was more influential than other sources.

4.2.3 Decisions and steering

With this review we focus on the inter-agent mechanism by which emotions spread, but the effective spread often also depends on the interaction between the emotional state and the behaviour of agents. For example, a person who becomes scared may move faster than a calm person, and in doing so may interact sooner with people that are further away, affecting the dynamics of the contagion process. In reality people display a broad variety of behaviours, and what action is decided upon by a person depends both on the internal state as well as the context. However, modelling the complete diversity of behaviour, especially in a crowd, is both unrealistic and often not relevant for the aims of the research.

Looking at Table 2, most of the included studies simulate agents that move through space, especially those that focus on evacuation. The emotional status of agents affects steering decisions by adjusting the speed and/or direction of the movement, either directly or indirectly by adjusting the grouping behaviour, beliefs or goals of an agent. Therefore, the effect of contagion is often measured as the time till an agent has escaped, group-level entropy, the local density (congestion) or the chosen trajectory.

There are many methods to model the decision-making or steering process of an agent and many ways that emotion can impact this process. For recent reviews that discuss decision-making and steering in agent-based crowds see [43–45]. This diversity is also reflected in the studies examined in the present paper as shown in Table 2. In about a third of the models, agents apply simple if–then based rules to make decisions while a quarter implements a cognitive decision, often based on the Believes, Desires and Intensions (BDI) framework. To model the movement of agents, cellular automata are popular as well as modelling agents as self-driven particles that are steered by surrounding and internal forces. Also global and local path planning algorithms are frequently chosen to steer agents, where we encountered the RVO (reciprocal velocity objects) model most frequently.

4.2.4 Personality

Of the examined studies the individual trait most frequently considered to affect emotion contagion is the personality of an agent. These models often assume personality characteristics affect not only the cognitive processes of an agent, but also the receiving, processing and expression of affective information. This means that most contagion mechanism include a parameter for the emotional expressivity of agents and a parameter for the susceptibility of agents to the emotional expressions that are perceived. About half of the studies that include personality in the contagion process do this by defining susceptibility and expressivity characteristics for the agents. The other half implement the OCEAN (Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism) model, that defines a five-factor personality profile for each agent from which the susceptibility and expressivity are derived.

4.2.5 Social relationships and roles

People in a crowd are connected with each other on many different levels and rates. Where for example models based on fluid dynamics view the crowd as a homogeneous mass, the power of the individual-based model is to view the crowd as a collection of separate entities that can be connected in various ways. In crowds people frequently form small groups, travelling with friends, family or co-workers, or identify with large groups such as a class, company or a football club and possess a cultural background. Von Scheve and Ismer [28] argue that sharing such connections promotes contagion via face-to-face contact and increases the likelihood to appraise an event in a similar manner and should be considered in the context of collective emotion. Moreover, these connections are not limited to people that are physically near each other in the crowd, but nowadays extend to an online identity and a social network that may connect parts of the physical crowd that are not spatially close.

Table 2 shows that several studies have considered how the social strength between agents affects emotion contagion, via aspects like intimacy, confidence and trust. The assumption of these studies is that a stronger intimacy, confidence or trust between two agents causes emotion to flow more easily. Next to this individual-based view on relationships, also general social roles are considered in the contagion process that imply a social relationship. In the evacuation domain we found the roles of parents that form close emotional and behavioural pairs their children, leaders that guide the emotions and behaviour of followers and authorities that calm and inform people. In scenarios that involve aggression there were also the roles of policing authority that tried to neutralize aggressive agents and protect others, as well as activists that threaten or incite others.

4.3 Mechanisms of emotion contagion

In this section the mechanisms are analysed by which emotions spread directly from agent to agent. The studies are categorised based on several features of the contagion mechanism.

The characteristics of each category and the implementations of studies in them are discussed per category. Note that the equations discussed from the examined models are often reformulated to focus on the process of emotion contagion and facilitate the comparison among different implementations. A list of frequently used symbols can be found in Table 3.

4.3.1 Group statistic

What the models in this category have in common, is that agents update their level of emotion according to a local statistic of a group, like the maximum or average level of an emotion, without considering variation in the impact of neighbours on an agent. Table 4 gives an overview of the simulation characteristics of the studies in this category. Note that the column 'comparison' here and in following tables signifies any direct comparisons against other models that contain a mechanism of emotion contagion.

4.3.1.1 Increase to maximum With the ESCAPES model Tsai et al. [46] propose a baseline mechanism for emotion contagion based on a simple set of rules suggested by Hatfield et al. [47], namely that 1) Agents inherit the maximum level of emotion that is locally present, 2) unless an authoritative figure is near in which case its level of emotion is adopted. It follows that emotion contagion between regular agents can only result in an increase of emotion. In [48] the authors simulated the spread of fear at an airport terminal, measuring the impact as the number of collisions among the agents to represent the level of chaos. They found that without authority figures to calm the travellers, emotion contagion more than doubled the number of collisions. In [46] they compare the ESCAPES model against the ASCRIBE model by Bosse et al. [49] and the model by Durupinar et al. [40] by simulating two real incidents of panic in crowds and comparing the trajectories of the agents to those traced in

Table 3 List of commonly used mathematical symbols in the present review

Symbol	Meaning
E	Level of an emotional state for an agent
ΔE	Change in the level of emotion
R	Agent that receives emotion
S	Agent that sends emotion
N	Set of local agents that contribute to emotion contagion
N	Number of agents in set N
T	Time step
D	Distance
$\boldsymbol{A}_{\mathrm{s}}$	Average level of an emotion of all senders in group N
ε_{s}	Emotional expressivity of the sender
δ_{r}	Emotional susceptibility of the receiver
d	Emotion dose
γ_{sr}	Emotional connection strength between a sender and receiver
α_{sr}	Channel strength between a sender and receiver
M^{x}	Mood factor of an agent where x is replaced by the factor identifier
φ^{x}	Personality factor of an agent where x is replaced by the factor identifier

Table 4 Simulation characteristics of studies classified as the group-statistic type

Study	Subtype	Scenario	Max. #agents	Validation using real data	Comparison
Tsai et al. [46]	Increase to maximum	Evacuation (airport terminal)	200	–	Against [40, 49]
Liu et al. [50]	Increase to average	Evacuation (school & supermarket)	400	Video of evacuation	Against [40]
Liu et al. [51]	Increase to average	Evacuation (supermarket)	500	–	–
Liu et al. [52]	Increase to average	Evacuation (hospital)	400	–	–
Aydt et al. [53]	Increase to average	Protest (embassy)	126	–	–
Xu et al. [54]	Adjust to average	Undefined (open space)	300	–	–

videos of the incidents. They concluded that the ASCRIBE model yielded a lower deviation compared to the other two models.

4.3.1.2 Increase to average The common factor in the following studies is that an agent is only affected by emotion contagion if the average level of emotion of neighbours is higher than its own level of this emotion. The studies however differ in how the impact of contagion is calculated.

Liu et al. in [50] consider the contagion of fear during the evacuation of a supermarket due to fire. Only if panic locally (A_r) is stronger than that of the receiving agent (E_r), its level of fear is increased depending on the difference between the local average and its own level of emotion, divided by the number of influential neighbours (n_r). This is modulated by how susceptible the receiving agent is (δ_r) times adjustment parameter w. The susceptibility is determined by the personality type of the agent that derived from the OCEAN model. Instead of the five-factor profile that is commonly used in other studies, the authors simplify the personality type to one of the factors of the OCEAN model, such as an Neurotic-type personality, which translates in a single value for the susceptibility for all agents with this type.

$$\Delta E_{rfear} = \frac{\left(A_{rfear} - E_{rfear}\right)}{n_r} w\delta_r \tag{1}$$

Because emotional change is proportional to the number of neighbours, the same average emotion at higher density would result in a lower rate of contagion. Why this was chosen is not clearly stated. The authors find that moderate contagion distributes the panic in a way that increases evacuation efficiency, whereas strong contagion results in congestion at the exit. Therefore, the authors propose the level of contagion needs to be controlled to improve safety during evacuations. They also compare their model against the epidemiological model of Durupinar et al. [40]. However, because the authors do not set a similar perception model, these results do not truly compare the performance of the contagion mechanisms.

In [51], Liu and colleagues again consider an evacuation scenario from a supermarket. Compared to [50] they have changed how susceptibility affects emotion contagion as shown in the equation below. Also, each agent is assigned a five-factor personality profile based on the OCEAN model ranging from -1 to 1. To determine the value of δ_r these axes are condensed based on the assumed effect each axis has on the contagion process. The authors state a profile with negative values for conscientiousness and expressiveness, and positive values for agreeableness and neuroticism increases the susceptibility to emotions of others, yet they do not provide further details on the exact mapping. Despite these differences, their conclusions about the effects of emotion contagion are similar to [50].

$$\Delta E_{rfear} = \frac{\left(A_{rfear} - E_{rfear}\right)}{n_r} \left(1 + \exp\left(\left|\delta_r\right|\right)\right) \tag{2}$$

In [52], Liu et al. simulate the contagion of two emotions, fear and hope, during the evacuation of a hospital following an earthquake. The fear level for receiving agent is determined by the strongest of three components: 1) the distance of the agent to the door of the building relative to the safe zone (D_{danger}/D_{total}), 2) the magnitude of the earthquake (m/m_{max}) and 3) the average level of fear of its neighbours (A_{fear}) times regulation coefficient k_1 (Eq. 1). The level of hope is determined by the highest value of two components, namely 1) the distance to the safe zone and 2) the average level of hope of the neighbouring agents (A_{hope}) times regulation coefficient k_2 (Eq. 4). $\alpha, \gamma, \beta, \omega$ and θ are personality coefficients and vary between 0.5 and 2 depending on the personality of an agent. Similar to [51], the personality is set by a five-factor OCEAN profile, though no mapping is presented of how these factors translate to the parameters in the equation below. In this study, the authors mainly focus on creating a realistic 3D visualization of the evacuation to provide an environment for safety education.

$$E_{r\,fear} = \max\left\{\cos^{\alpha}\left(\frac{D_{danger}}{D_{total}} \times \frac{\pi}{2}\right), \sin^{\beta}\left(\frac{m}{m_{\max}} \times \frac{\pi}{2}\right), \sin^{\gamma}\left(k_1 \times A_{r\,fear} \times \frac{\pi}{2}\right)\right\} \tag{3}$$

$$E_{r\,hope} = \max\left\{\cos^{\omega}\left(\frac{D_{total}-D_{danger}}{D_{total}} \times \frac{\pi}{2}\right), \sin^{\theta}\left(k_2 \times A_{r\,hope} \times \frac{\pi}{2}\right)\right\} \tag{4}$$

Aydt et al. [53] consider emotion contagion as an appraisal process. The average emotion of neighbours is interpreted by the receiving agent according to an appraisal-emotion mapping where the triggered appraisal pattern always leads to an increase of emotions. The vector L contains the results of the mapping for each emotion. The change of each emotion in the receiver is determined by the inverse of L times the susceptibility (S_r) to each emotion. The susceptibility for a particular emotion depends on the personality of the receiver. Therefore, the same trigger may result in different emotional responses in a group.

$$\Delta E_r = S_r(1 - L) \tag{5}$$

While this model allows for a range of emotions and appraisal types, in their simulation the authors focus only on the spread of anger during a protest at an embassy. The appraisal pattern for anger is triggered in a receiving agent, if the average level of anger is higher in the surrounding agents than in this agent. The agents vary in how strongly this trigger increases their anger. To test the model, Aydt et al. let nonexpert participants play a serious game in the role of security personnel that are tasked to keep the protest peaceful by choosing which agents to pacify. They conclude their model can simulate crowds that differ in their difficulty to control and therefore could provide a basis for more extensive games that can be used for training purposes. They point out however that careful consideration is necessary in the contagion of multiple emotions to prevent agents from experiencing strong emotions that are contradictory at the same time (e.g. happy and sad).

4.3.1.3 Adjust to average Contrary to the previous studies, emotion contagion in the model of Xu et al. [54] can also decrease the emotion of the receiver. For this the authors consider two opposite emotions that are inversely related to each other via $E_{neg} + E_{pos} = 1$. If the whole group of neighbours is on average more negative than positive ($A_{neg} > A_{pos}$), the negative emotion (E_{neg}) of the receiving agent will increase with the negative influence of its neighbours (I_{neg}) while the positive emotion (E_{pos}) will decrease with this negative influence. This relation is reversed for the positive influence (I_{pos}) if on average there is more positivity than negativity. Note that this does not depend on the emotional state of the receiver.

$$\begin{aligned} \Delta E_{neg} &= \begin{cases} I_{neg} & A_{neg} > A_{pos} \\ -I_{pos} & A_{neg} < A_{pos} \end{cases} \\ \Delta E_{pos} &= \begin{cases} -I_{neg} & A_{neg} > A_{pos} \\ I_{pos} & A_{neg} < A_{pos} \end{cases} \end{aligned} \tag{6}$$

The negative influence I_{neg} is the average negativity of only the subset of neighbours N_{neg} who are more negative than positive ($E_{neg} > E_{pos}$). Similarly, the positive influence I_{pos} is the average positivity of the group of nett positive ($E_{neg} < E_{pos}$) neighbours N_{pos}. These are modulated by bias parameters b_{neg} and b_{pos} respectively, where $b_{neg} + b_{pos} = 1$.

$$\begin{aligned} I_{neg} &= \frac{\sum_{s \in N_{neg}} E_{neg}}{N_{neg}} * b_{neg} \\ I_{pos} &= \frac{\sum_{s \in N_{pos}} E_{pos}}{N_{pos}} * b_{pos} \end{aligned} \tag{7}$$

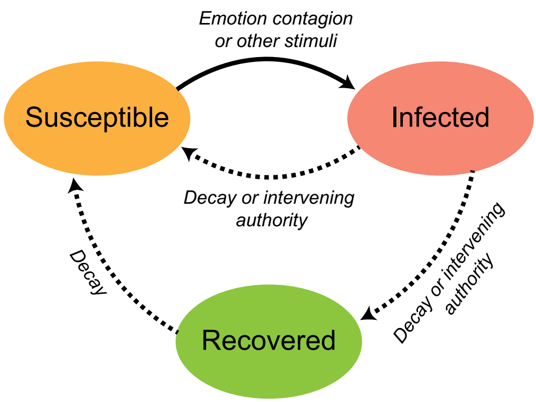
Although the authors do not simulate a specific scenario, they were inspired by observations of the incident of mass panic at the Love Parade in which some visitors tried to move quickly and some slowly. This dualistic approach is reflected in the way the positive and negative emotions are inversely related and the strongest of the pair sets the walking speed of the agent in a categorical way. While this approach prevents the problem of agents having multiple contradictory emotions as remarked by [53], the application of this approach seems limited to scenarios with only two relevant states.

4.3.2 Epidemiological

Generally speaking, epidemiological models are used to model the spread of an influence in a population [55]. What spreads in these models, and in what kind of population, covers a wide range of topics, including biological diseases, computer viruses, political and religious following, crime, financial crises and gossip [56, 57]. A shared factor is that the state of a member of the population is categorical: one either is or is not infected. This state however does not have to be binary. An agent can for example be susceptible to a disease, then be infected by it and afterwards be immune to it for some period before returning to a susceptible state.

Similarly, different states are used in epidemiological models of emotion contagion (Fig. 4). In the simplest form, used in [58, 59], a binary state is considered: Susceptible or Infected (SI). Once an agent becomes infected it will remain infected and perform the associated behaviour. More complex types are SIS used in [40, 42, 60–65], and SIRS used in [66–70]. The first two letters stand for Susceptible and Infected. The R signifies the addition of a recovered state in which the agent is immune for reinfection with the emotion.

Fig. 4 Typical transitions in emotional states of agents in epidemiological models. The solid arrow is present in all models



The addition of the last S signifies a transition back to the susceptible state, thus allowing individuals to become infected multiple times.

The transition from a susceptible to an infect state represents the contagion of emotion, yet the mechanism that governs this transition varies. We identified two subtypes that we named stochastic doses and individual properties. Table 5 gives an overview of the simulation characteristics of the studies in this category.

4.3.2.1 Stochastic doses The mechanism we termed stochastic doses is also referred to as the Durupinar model, who first introduced this type of epidemiological emotion contagion [71]. While the publication date excluded this study from the present review, we included several later studies that are based on this mechanism. The complete model is relatively complex, but in its basic form contagion occurs via 'doses' of emotion that susceptible agents receive from perceived infected agents. The size of each dose (d_s) is drawn randomly from a log-normal distribution. The total dose that affects the receiver (d_r) is the sum of all doses it received over the last k timesteps.

$$d_r(t) = \sum_{t'=t-k+1}^{t} d_s\left(t'\right) \tag{8}$$

The receiving agent becomes infected if the total dose (d_r) is larger than a susceptibility threshold (δ_r). The susceptibility threshold is also drawn from a log-normal distribution. The characteristics of the log-normal distributions from which the thresholds and doses are drawn are often determined by characteristics of the agents such as their personality.

$$E_r(t) = \begin{cases} d_r & d_r(t) > \delta_r(t) \\ 0 & else \end{cases} \tag{9}$$

The P-SIS model of Cao et al. [62] closely follows this basic form, except that upon infection the emotion of the agents becomes one instead of the value of the total dose. They consider only the spread of fear and the distribution out of which the susceptibility threshold is drawn is determined by the agent's neuroticism characteristic from the OCEAN model. The authors combine this contagion model with the social force model to steer the agents and simulate evacuations in an office environment. They find that the addition of emotion contagion results in a longer evacuation time compared to just the social force model due to increased congestion around the exits, especially as the number of agents increases. The authors conclude that their model realistically simulates pedestrian flow but present no empirical foundation for this conclusion.

Zou et al. [63] use the P-SIS model of [62] to simulate an evacuation following the spread of a toxic gas in a building. They combine the contagion of panic with the transmission of information via the interactions of regular agents, distribution by authorities and the dispersion of the gas itself. Regarding emotion contagion, they conclude that emotions can have a large impact on group behaviour during evacuations and should be considered in emergency planning. Also, they find that introducing a small percentage of agents that calmed and informed others was effective to strongly reduce the number of injuries and collisions and lower evacuation time.

In a follow up on [71], Durupinar et al. [40] simulate emotion contagion during a protest and the rush into a store during a sale event. The contagion process involves 22 emotions as defined in the OCC model. Like Aydt et al. [53], the authors remark that the contagion of multiple categorical emotions poses challenges with regard to how the emotions

Table 5 Simulation characteristics of studies classified as the epidemiological type

Study	Subtype	Scenario	Max. #agents	Validation using real data	Comparison
Cao et al. [62]	Stochastic doses	Evacuation (office)	600	–	–
Zou et al. [63]	Stochastic doses	Evacuation (indoor)	350	–	–
Durupinar et al. [40]	Stochastic doses	Protest & sale event	240	–	–
Du and He [69]	Stochastic doses	Evacuation (subway station)	1000	–	To [40]
Mao et al. [59]	Stochastic doses	Evacuation (supermarket, street, stadium)	1400	–	To [40]
Xu et al. [61]	Stochastic doses	Evacuation (street, room, mall, subway)	300	Video of evacuations	To [40, 72]
Xu et al. [60]	Stochastic doses	Evacuation (street)	50	Video of evacuations	–
Tian et al. [58]	Stochastic doses	Evacuation (school, office, airport, station)	500	Video of evacuations	To [60, 62]
Fu et al. [66]	Individual properties	Undefined (open space)	2000	–	–
Huang et al. [67]	Individual properties	Protest (open space)	850	–	–
Li et al. [65]	Individual properties	Protest (various)	200	Video of antagonistic incidents	To [67]
Xiong and Jiang [64]	Individual properties	Aggression (hospital)	100	–	–
Lv et al. [68]	Individual properties	Political gathering (city square, street)	Not stated	Video of political gatherings	To [40]
Xiao et al. [42]	Individual properties	Evacuation (room)	800	–	–
Zhou et al. [70]	Individual properties	Evacuation (subway, arena, museum)	200	–	To [62, 59]

should determine the behaviour and emotional expression of the agent. Taking the strongest emotion to affect behaviour and contagion results in erratic changes and oscillations according to authors, while adding up emotions to a single value is not possible for all 22 emotions. Their solution is to implement a dimensional component (PAD model) that acts as an intermediary between the emotion, behaviour and personality components. This is accomplished by mapping the values for 22 emotions of the OCC model to one dominant emotion that is either of eight combinations of the polarities of the factors in the PAD model (for example ‘relaxed’ is defined as P + A- D +). The chances that an infected agent expresses emotion and that a susceptible agent digests this emotion depend on the agent’s extraversion and empathy respectively, which are determined from the personality of the agent using the OCEAN model. The authors simulate a protest scenario and a competitive shopping scenario. The agents select goals and attitudes based on their role and personality, and to make decisions, a behaviour tree is used. Evaluating specifically the contagion model, the authors find that the personality strongly impacts the spread of emotions, where strongly empathetic and expressive crowds escalate to an angry mob while anger does not spread without empathy and expressivity. In a crowd with diverse personalities, anger first spreads but eventually dies out. The authors conclude their model offers a versatile solution to include the psychology of agents in crowd simulations, but do not offer empirical evidence in this study.

Du and He [69] use the emotion contagion mechanism and psychological features as presented in [40], and combine it with a physiological need for personal safety that affects its emotional state, as well as graph-based path planning that is affected by the emotional state of an agent. The authors simulate an evacuation from a subway station and compare their model to that of Durupinar et al. [40]. The authors find that the performance of the models is similar. They observe the share of negative emotions first rises due to contagion but after some time falls due to decay, only to rise again after a second emergency. They conclude that the addition of physiology and a path-finding algorithm makes the model more realistic in an evacuation setting, though no data is presented in this study that supports this conclusion.

Mao et al. [59] extend upon [40] by considering social relationships in the emotion contagion and the decision making process. Specifically, additional to the local spread of emotion, they introduce a process for emotion contagion among peers based on their social relationship. This process of emotion contagion functions similarly as the contagion among neighbours, except that the susceptibility is not determined by the empathy of the susceptible agent, but by the intimacy between the susceptible agent and the infected agent. The authors state that the intimacy of two agents at a specific timestep depends on the time they communicate, the strength of their relationship determined from how close their daily trajectories are, cognitive rapport and approbation degree. The study however does not fully explain how these factors are determined. The authors perform several experiments to study how emotional relationships among peers affect the decision making in evacuation scenarios. They compare their model to the model by Durupinar et al. in [40] and find that the heterogeneity caused by the contagion among peers and the search behaviour when peers lose each other causes less congestion than in the simulations with Durupinar’s model that does not consider social relationships.

Xu et al. [60] test the contagion mechanism by Durupinar et al. [40] in a multi-hazard environment. They combine emotion contagion with global and local path planning based on an extension of the RVO model that takes a multi-hazards environment into account. They simulate a variety of outdoor evacuation scenarios based on video footage. Comparisons of the group-level tendency to aggregate or dissipate as well as the individual trajectories between their model and the videos reveal that their model can mimic escape behaviour without needing to set specific goals for the agents to travel to. The authors conclude that their model is robust for different types of evacuation scenarios and can deal with multiple sources of hazard. Yet they find it cannot fully capture the individual variation in the scenes, that results from factors like prior experience, knowledge and personality traits other than susceptibility and expressivity, and influences the behaviour of the agents.

In [61], Xu et al. explore the relationship between physical exertion and psychological stress via the heart-rate changes in evacuation scenarios. The first part of the emotional change of an agent consists of three components. These are 1) the distance between the hazard source and the agent, 2) emotion contagion as per the method of Durupinar et al. [40] and 3) emotional decay. The second part of emotional change is the effect of physical exertion, that is established by calculating the change in heart-rate due to physical activity and the level of fear of the agent. The authors simulate evacuations in a large number of scenarios by combining the physiological and emotion model of the agents with the movement model proposed in [60]. Using real videos of evacuations selected from a public dataset, they compare their model against those of Durupinar et al. [40] and Neto et al., including versions of these models with physical exertion [72]. They find that the similarity of their model of in terms of average speed, entropy and spatial deviation of the dominant path of the real crowd was higher than that of the other two models that scored similarly on most metrics. While the authors conclude that their model produces realistic movement of crowds, they do not have the data to validate the emotional and physical components directly. They suggest this may be achieved by tracking biometric data during an emulated incident in a crowd.

Tian et al. [58] propose a new use of the Durupinar model [40] by defining a close relationship between emotion and knowledge. The knowledge of hazard sources and the environment directly determines the emotional state of the agent and it is the knowledge that infects agents. The emotions of a receiver are determined by emotion contagion and by its knowledge, where the authors assume more knowledge leads to lower levels of fear. The contagion component does not involve the Durupinar model but simply depends on the distance between an infected and susceptible agent and the emotion of the sender from the previous timestep. This differs significantly from the other approaches examined in the present review because emotion contagion dependents strongly on cognitive processes as it assumes only people with knowledge are emotionally infectious. For the details of this mechanism we refer to [58]. The authors simulate a variety of evacuation scenarios and compare their model to several videos of real evacuations and to the models of Xu et al. [60] and Cao et al. [62]. They find that their model closer resembles the evacuation videos than the other models based on deviation in the average speed and trajectory. In particular the authors conclude that the dynamics of individual knowledge led to uneven trajectories that match those in the evacuation video much closer than the other two models that do not consider knowledge.

4.3.2.2 Individual properties In the second mechanism introduced by Fu et al. [66], the transition from susceptible to infected depends on properties of the sender and receiver, and does not involve stochasticity. The panic of susceptible agents increases if there are infected agents nearby. When the emotion of an agent reaches a predefined threshold value, the agent will transition to an infected state. In the infected state the agent only transmits emotion. An infected agent transitions to the recovered state and back to the susceptible state after a time that is drawn from a normal distribution that represents variation in personality characteristics.

The (positive) change in emotion (E_r) of the susceptible agent for each time step is the sum of the contagion from all infected neighbours in set N_r. The emotional influence of the sender on the receiver is oppositely related to the distance D_{sr} between the two agents. E_s is the level of emotion of the sender. The expressivity of the sender (ε_s) and the susceptibility of the receiver (δ_r) are personality characteristics of the agents. The values of E_s δ_r and ε_s range from 0 to 1.

$$\Delta E_r = \sum_{s \in N_r} \left[1 - \frac{1}{1+\exp\left(-D_{sr}\right)}\right] \cdot E_s \cdot \delta_r \cdot \varepsilon_r \tag{10}$$

Fu et al. [66] simulate an unspecified spread of panic in large crowd that performs a random walk in a cellular automaton. They find that model tends to oscillate with waves of infection around a mean value that depends on the chances that infected agents recover and for recovered agents to become susceptible again. If the chance to recover is very low for infected agents, movement results in a higher average percentage of infected agents. From this the authors recommend studying whether controlling the movement of crowds may help control outbreaks of emotion.

Huang et al. [67] study collective violence following the contagion of societal grievance. They present a model called ABEC that is an extension of [66]. For this the authors add component β to the contagion equation that represents the transmission rate of an event that triggered the grievance, arguing the nature of the event affects how well emotions spread in the crowd. They also introduce policing agents that can arrest infected agents that behave violently when they outnumber these agents locally. This takes away sources of emotion from the system temporarily. The authors find a non-linear evolution of violence. First small clusters of violence emerge that grow over time to large clusters, but as some agents recover, these break up into smaller clusters before reaching an equilibrium state. While the authors recognize validation is needed, based on their results they suggest police could attempt to separate the susceptible agents physically from the pockets of violence or to appease the grievance before it escalates to violence.

$$\Delta E_r = \left[1 - \frac{1}{1+\exp\left(-D_{sr}\right)}\right] \cdot E_s \cdot \delta_r \cdot \varepsilon_r \cdot \beta \tag{11}$$

Li et al. [65] propose the ACSEE model by implementing the contagion model from Fu et al. [66] in a framework of evolutionary game theory. They simulate antagonistic scenarios where there are neutral civilians (susceptible) as well as activists (infected) and police that can choose to confront or cooperate with each other. Each agent has an emotion variable that ranges from negative at -1 to positive at 1. All agent types are affected by emotion contagion, but only activists and police affect the emotions of others. Moreover, when the level of emotion of a civilian passes a threshold, it becomes an activist and vice versa. The activists and police can deactivate other agents representing antagonistic behaviour.

To validate their model, the authors compared it to videos of real antagonistic incidents on YouTube drawn from a public dataset in two ways. In the first method they measured the dominant path and the entropy in both the model and the video and compared this to establish a similarity score. In the second method they asked nonexpert participants to view the model output and the real video and rate the similarity. In both methods they performed simulations with and without emotion contagion, and also included the ABEC model [63] for comparison. They conclude that their model with emotion contagion outperforms the alternatives that were tested, but note that there was a significant divergence between the antagonistic behaviour in the video and that of the model. They attribute this to two factors. The first is that the quality of the videos was low and hindered the accurate inference of the start scenario. The second is that game theory assumes all actors are rational, while some people in the scene like are not and chose a suboptimal strategy.

Lv et al. [68] extend the contagion mechanism of the model of Fu et al. [66] with OCEAN model. The susceptibility of the receiver is defined as its empathy that is calculated using all five factors of the OCEAN model. The expressivity of the sender depends only on the extraversion factor. Using the social force model for navigation and a link between the opinions and emotion of an agent, they simulate two types of political gatherings. The first is a non-moving gathering at a city square and the second is a moving parade. The authors compare their model against that of Durupinar et al. [40] in the fixed scenario and find that the emotional change is more distributed with a few responding strongly but also some agents that respond mildly or are uninfected, while the Durupinar model showed a more polarized emotional response. They also compared their model against video of a real public parade. The authors conclude that the behaviour in the model reasonably resembles that in the video, but that this may be improved with knowledge of the personalities of the people in the video.

Xiao et al. [42] focus on the role of perception in the process of emotion contagion. They consider two domains of perception, a visual field of view and a nonvisual domain that consists of the remaining field around the agent. The authors assume that visual stimuli have a stronger effect on emotion than the nonvisual stimuli, and that both effects decrease with distance. They base their contagion mechanism on that by Fu et al. [66] but they split the contagion by modality and do not consider the degree of susceptibility and expressivity of the agents. The agents change between the susceptible and infected state based on a global threshold where their state determines the behaviour strategy. For details of this process, we refer to the study itself. The authors implement this mechanism in a cellular automaton and describe the movement of the agents as the chance for an agent to transfer to adjacent cells. They simulate evacuations from various rooms and vary the perception characteristics and infection threshold. They find a relation between the perception range and the infection threshold where wider range has a negative effect on the evacuation time with a low infection threshold and positive effect on evacuation time with a high infection threshold. The author conclude however that empirical evaluation is necessary to verify the significance of these findings.

Zhou et al. [70] extend the model by Fu et al. [66] by considering the spread of six categorical emotions and integrating the OCEAN personality model and an intimacy factor in the contagion process. The effect of contagion is calculated similar to Eq. 10, but the susceptibility of a receiver (δ_{sr}) is determined by the level of intimacy, which consists of the strength of the relationship (α_{sr}), the difference in personalities (h_{sr}) and a factor that represents cognitive rapport and approbation (q_{sr}). The potential impact (I_{sr}) of emotion contagion is determined by modifying the effect of contagion (E_{sr}) by the susceptibility of the receiver, based on the accumulation of the accident experience (χ_{sr}) and its personality (φ_r). The potential impact is only added to the emotion of the receiver if it passes a threshold (λ_{sr}). This threshold is a function of the intimacy (δ_{sr}) and the distance (D_{sr}) to the sender, that is not further specified by the authors.

$$\delta_{sr} = \alpha_{sr}\left(h_{sr} + q_{sr}\right) \tag{12}$$

$$I_{sr} = E_{sr}(\omega \cdot \chi_r + \psi \cdot \varphi_r) \tag{13}$$

$$\Delta E_r = \begin{cases} I_{sr} & E_{sr} > \lambda_{sr} \\ 0 & else \end{cases} \tag{14}$$

To study the impact on the evacuation process, Zhou et al. simulate various evacuation scenes where the emotions of agents are initialized based on their personality and their behaviour is based on a path planning algorithm influenced by emotion. They compare the performance of their model against that by Cao et al. [62] and Mao et al. [59] and find that their model leads to lower evacuation times. The authors attribute this to the knowledge of the environment that comes from the addition of the path planning algorithm. Further they ask nonexpert participants to score how realistic the visual output generated by the models looks. Based on the answers of the participants and the computational efficiency of their model, the authors conclude their model is superior to the other examined models. However, their method leaves open how close the simulations come to resembling real incidents, as they did not compare the simulations to empirical data.

Different from the other studies examined in this subsection, Xiong and Jiang [64] propose a model that is not based on the model by Fu et al. but where emotion contagion is entirely determined by the level of intimacy between agents. The dose a susceptible agent receives at a timestep is determined as the number of infected agents (n) weighed by the nature of their relation to the susceptible agent. The relation types include in order of decreasing influence: family (W_h), neighbours (W_n), friends (W_f), colleagues (W_c), media (W_m), the values of which add up to one. When the total dose (d_r), determined by its susceptibility (δ_r), comes above the threshold value of the receiving agent, it transitions to an infected state, otherwise it remains susceptible. Infected agents perform the same process to determine if they stay infected.

$$d_r = W_h n_h \cdot W_n n_n \cdot W_f n_f \cdot W_c n_c \cdot W_m n_m \tag{15}$$

$$E_r = \begin{cases} 0 & d_r < \delta_r \\ 1 & d_r > \delta_r \end{cases} \tag{16}$$

The authors simulate a scenario inspired by a series of incidents of aggression against medical doctors. They identify three stages in their simulations. First the conflict attracts quickly more people, then the conflict remains relatively stable over a period of time before finally breaking apart. The authors conclude this general pattern follows that of the real incidents.

4.3.3 Dyadic relations

The studies discussed in this section all apply a concept of quantitative emotion contagion in pairs of individuals. What makes this approach different from the local statistic category is the idea that individuals do not exchange emotions with people around them equally. The models in this category consider various pair-specific properties that make that the ability for emotion to flow from each sender to a receiver is different. These properties include personality, social relationship and distance. While these aspects are also considered in the epidemiological-type models, those lack the continuous and bidirectional nature of the models in the present category. This different view on the contagion process in theory makes the models in this category suitable for more subtle scenarios of emotion contagion, but arguably also more complex. Table 6 gives an overview of the simulation characteristics of the studies in this category.

4.3.3.1 Thermodynamics-based Bosse et al. [49] proposed a contagion model called ASCRIBE that is inspired by equations of thermodynamics. ASCRIBE and prior versions of this model form the basis for most of the studies examined in this section. In this model, the emotional change in a receiver (ΔE_r) due to contagion is determined by two components. The first expresses how easy emotion can flow through a connection between two agents. The second represents the emotional influence that the sender has on the receiver.

$$\Delta E_r = \langle connection \rangle \cdot \langle influence \rangle \tag{17}$$

The total connection strength to a receiver (Γ_r) is the sum of the connections between the receiver and each sender in group N. Each connection is determined by the expressivity of the sender (ε_s), the channel strength (α_{sr}) determined by the reciprocal of the distance between the agents and the susceptibility of the receiver (δ_r). Susceptibility and expressivity are personality characteristics of the agents.

$$\langle connection \rangle = \Gamma_r = \sum_{s \in N_r} \gamma_{sr} \tag{18}$$

$$\gamma_{sr} = \varepsilon_s \alpha_{sr} \delta_r \tag{19}$$

The influence from the senders on the receiver is determined by the tendency of the receiver to absorb or to amplify emotions, set with parameter η_r. Absorption represents the tendency of people to emotionally align with others. Amplification represents a process in which people with similar emotions escalate ($\beta_r > 0.5$) or dampen their emotions ($\beta_r < 0.5$). This makes amplification the driving force behind the occurrence of emotional spirals in the model, while absorption drives the emergence of collective emotion. E_s^* is the sum of the senders' emotions weighted by their connection strength.

$$\langle influence \rangle = \eta_r(\langle amplification \rangle) + \left(1 - \eta_r\right)(\langle absorption \rangle) \tag{20}$$

$$\langle amplification \rangle = \beta_r\left(1 - E_s^*\right)\left(1 - E_r\right) + \left(1 - \beta_r\right)\left(E_s^* E_r\right) - E_r \tag{21}$$

$$\langle absorption \rangle = E_s^* - E_r \tag{22}$$

$$E_s^* = \sum_{s \in N_r} \frac{\gamma_{sr} E_s}{\Gamma_r} \tag{23}$$

Bosse et al. [49] simulate the outbreak of panic that occurred during a memorial gathering on a square in the Netherlands and compare their model to video footage. For this they traced the paths of 35 individuals in the real crowd and compared that to agents in a simulation that resembled the environment in the video. They measured the deviation to the traced paths and found that the ASCRIBE model with emotion contagion deviated significantly less than without emotion contagion, or two other models that did not include emotion contagion. The main difference was that ASCRIBE with

Table 6 Simulation characteristics of studies classified as the dyadic-relations type

Study	Subtype	Scenario	Max. #agents	Validation using real data	Comparison
Bosse et al. [49]	Thermo-dynamics	Evacuation (office, city square)	30	Video mass panic incident	–
Bordas and Tschirhart [73]	Thermo-dynamics	Undefined (open space)	100	–	–
Sharpanskykh and Zia [74]	Thermo-dynamics	Evacuation (train station)	1000	–	–
Jutte and van der Wal [75]	Thermo-dynamics	Soccer match (arena)	100	Heart-rate data and survey	–
Neto et al. [72]	Thermo-dynamics	Undefined (closed space)	111	–	–
Saunier et al. [76]	Thermo-dynamics	Small group	1521	Video and survey data	–
Sakellariou et al. [77]	Thermo-dynamics	Evacuation (office)	2000	–	–
Sakellariou et al. [78]	Thermo-dynamics	Attendance (bar)	100	–	–
Mao et al. [79]	Thermo-dynamics	Evacuation (office, school, stadium)	1500	–	To [46, 62]
Rincon et al. [21]	Classical mechanics	Small gathering	10	–	–
Shao et al. [80]	Probabilistic	Public service failure (airport)	150	–	–
Bu and Yiyi al. [81]	Threshold	Aggression (open space)	500	–	–
Ta et al. [82]	Other	Evacuation (undefined)	50	–	–

emotion contagion captured the initial lack of response, because it takes time for the fear to spread through the crowd and for people to take action. From this the authors conclude emotion contagion has a significant effect on the evacuation process. However, also with emotion contagion there was a clear deviation to the paths of real people. They suggest this may be due to the simple navigation model that was used, which only considered traveling in eight directions, and a lack of individual variation in the parameter setting.

Bordas and Tschirhart [73] propose that the contagion strength between two agents depends on their personality, mood and social relationship. They use a simplified version of ASCRIBE where contagion depends on the connection strength as shown in Eq. 19, yet ε_s, α_{sr} and δ_r are derived differently. Expressivity of the sender (ε_s) is determined by personality factors conscientiousness (ϕ^C), extraversion (ϕ^E) and agreeableness (ϕ^A) from the OCEAN model. Susceptibility of the receiver (δ_r) depends on the mood factors arousal (M^A) and dominance (M^D) from the PAD model, and personality factors agreeableness (ϕ^A), openness (ϕ^O) and extraversion (ϕ^E). The study does not give argumentation for these ratios.

$$\varepsilon_s = \frac{-\varphi_s^C}{4} + \frac{\varphi_s^E}{2} + \frac{\varphi_s^A}{6} \tag{24}$$

$$\delta_r = \frac{M_r^A + M_r^D}{4} + \frac{\varphi_r^A - \varphi_r^O}{6} + \frac{-\varphi_r^E}{3} \tag{25}$$

Further, they assume that instead of the physical distance, someone is more influenced by others to whom they have a closer relationship (α_{sr}). They define relationships on three levels: the strongest is at a group-level (G), then at a crowd-level (C), and least strong is across multiple crowds (MC). An agent is alone or can be member of one level of which the parameter value is set to 1, the other parameters are set to 0.

$$\alpha_{sr} = \frac{1}{10} + \left(\left| \frac{(G_s + G_r)^2}{6} - \frac{C_s + C_r}{2 + (4C_s C_r)} - \frac{MC_s + MC_r}{6} \right| \right) \tag{26}$$

The authors explored their model by simulating different crowd compositions in an undefined scenario. Most notably they find that the different scales of social groups caused emotion to spread unevenly, where socially isolated individuals were infected later than those belonging to one of the groups.

Sharpanskykh and Zia [74] focus on the effect of emotion contagion on group decision making during the evacuation of a train station in which some agents receive information via personal devices. Contagion among agents occurs for the emotions fear and hope and affects the believe about the exits of the building. They propose a cognitive model based on the contagion mechanism in ASCRIBE, that they extend with the trust (τ_{rs}) of the receiver in the sender. The assumption of the authors is that when a receiver has a stronger trust in the source of the emotion the emotional connection becomes stronger. Trust in a neighbouring agent is updated by comparing information received from the sender with the believes of the receiver. The level of trust in the sender increases if the information and believes match, and decreases if they differ.

$$\gamma_{sr} = \varepsilon_s \alpha_{sr} \delta_r \tau_{rs} \tag{27}$$

The authors find that the informed agents develop into leaders followed locally by uninformed agents to form a group. Changes in believes are dampened by the spread emotion, that promotes the cohesiveness of subgroups. They conclude that this effect can be mitigated by increasing the number of agents in possession a personal device for accurate information.

Jutte and van der Wal [75] propose a cognitive model of contagion of pleasure and sadness among different types of soccer supporters, based on the contagion mechanism of ASCRIBE. In this study, sensing, processing and expression of emotion that make up emotion contagion are grounded in neurological processes in specific brain structures. Contagion occurs when an emotion expressed by the sender (Anterior Cingulate Cortex and Amygdala) reaches the sensor of the receiver and is processed by the Amygdala (represents the internal emotion). Besides susceptibility (Dorsal Striatum and Anterior Cingulate Cortex) the authors also consider the characteristic impulsiveness (ι_r) of the receiver that follows from the reduced ability to control emotions in the Orbitofrontal Cortex. Like the other personality characteristics, impulsiveness ranges from 0 to 1.

$$\gamma_{sr} = \varepsilon_s \alpha_{sr} \delta_r \iota_r \tag{28}$$

Jutte and van der Wal compare simulations of their cognitive model with data collected during a soccer match. They find emotion contagion occurs over the entire duration of the match but varies by emotion and supporter type, suggesting that emotion contagion is a relevant concept in everyday activities, not just extreme situations. This is supported by the resemblance of their model to heart-rate data of the supporters during a real soccer game.

Neto et al. [72] integrated the contagion mechanism of ASCRIBE in the BioCrowds platform for collision-free movement of agents. The framework they present gives a method for the contagion of multiple categorical emotions. Only the strongest emotion in an agent affects its actions by activating a goal associated with that particular emotion. Further, BioCrowds differentiates between subgroups in the crowd and the authors assume contagion is stronger between members of the same group. To reflect this, channel strength (α_{sr}) is formulated as the reciprocal of the distance (D_{sr}) attenuated by the group affinity (g_{sr}) that is shared between the agents. The authors do not suggest specific values for g_{sr}. Despite the extended model, Neto et al. only show basic simulations with one undefined emotion in which all agents belong to the same group.

$$\alpha_{sr} = g_{sr} \frac{1}{D_{sr}} \tag{29}$$

Saunier et al. [76] propose a simplified version of the mechanism in ASCRIBE by omitting amplification and weighing of the senders emotion as shown below. They compare their model against real data from an experiment with groups of five people. One of these persons was an actor that maintained a specific level of emotion in interaction with the participants. The emotional state of the participants was measured using video and surveys. The authors found that the emotions of the participant agents were pulled toward that of the actor agent and settled in equilibria around the emotion of the actor that was kept constant. They conclude that this pattern is consistent with the experimental data that found both the convergence in emotion and persistent individual variation.

$$\Delta E_r = \varepsilon_s \sum_{s \in N_r} \delta_r \alpha_{sr} (E_s - E_r) \tag{30}$$

Sakellariou et al. [77] also propose a simplified version of the contagion mechanism in ASCRIBE without amplification and combine this with a finite state machine. Change in emotion due to contagion is determined by the average absorption, namely the difference in emotion between agents weighted by their contagion strength.

$$\Delta E_r = \frac{\sum_{s\in N_r}\left(\frac{\gamma_{sr}}{\Gamma_r}\right)\cdot(E_s - E_r)}{n} \tag{31}$$

The authors simulate an evacuation from an office where fear spreads among the agents, some of which are followed by child agents that do not participate in the contagion process. They conclude that while validation is necessary, the emotional finite state machines with emotion contagion can produce believable behaviour of an evacuating crowd.

In [78] Sakellariou et al. extended the model of [77] with a two dimensional representation of emotion. The emotional state of an agent consists of a valence and arousal dimension (range -1 to 1) that form emotional space in which the emotional state of an agent can be represented as a single point location. In the contagion process, first the total emotion that is perceived by a receiver is calculated per dimension. This is defined as the sum of each percept of a sender weighted by the senders expressivity (ε_s) and the distance between the agents (α_{sr}). Then the perceived valence ($V_r{}^*$) and arousal ($A_r{}^*$) are translated to a change in the valence (ΔV_r) and arousal (ΔA_r) of receiver by considering the susceptibility of the receiver (δ_r).

$$\left(V_r^*, A_r^*\right) = \left(\sum_{s\in N_r}\left(\frac{\varepsilon_s\alpha_{sr}}{\sum_{c\in N_r}\varepsilon_s\alpha_{sr}}\right)\cdot V_s, \sum_{s\in N_r}\left(\frac{\varepsilon_s\alpha_{sr}}{\sum_{c\in N_r}\varepsilon_s\alpha_{sr}}\right)\cdot A_s\right) \tag{32}$$

$$\left(\Delta V_r, \Delta A_r\right) = \left(\frac{\delta_r^2\left(V_r^* - V_r\right)}{1+e^{-\delta_r V_r^*}}, \frac{\delta_r^2\left(A_r^* - A_r\right)}{1+e^{-\delta_r A_r^*}}\right) \tag{33}$$

The authors simulate the El Farol problem in which an agent will only enjoy a visit to a bar if less than 60% of the population decides to come to the bar, otherwise it results in negative sentiment. The agent will decide to visit if both its valence and arousal are positive. Additionally, emotion contagion takes place within ten subgroups of ten agents. They find that emotion contagion results in a higher average attendance because agents tended to align to the collective emotion, showing that emotion functions as a coordination mechanism.

Mao et al. [79] propose a model that is based on ASCRIBE and emphasizes the effect of within-group and between-group relationships during evacuation. Emotion contagion occurs within the group both among its members and from the leader to the members, where the latter has more impact. There are also authority agents that have a calming effect on agents. Further the agents can switch to another group that has a stronger emotional pull than the agent's own group. The authors have integrated the OCEAN personality model that determines the susceptibility and expressivity of agents and a path planning algorithm to steer the agents, which includes information about the density of the crowd. For brevity we refer for details of this extensive mechanism to [79]. They simulate evacuations from an office, school and stadium and find that emotion contagion causes a longer evacuation time, while calming authorities lower the evacuation time. They also compare the results against the ESCAPES model in [46] and the model by Cao et al. in [62]. The comparison against ESCAPES serves to highlight the decrease in collisions due to the path planning algorithm. Comparing the evacuation time of their model with the model by Cao et al., the authors conclude the latter results in more congestion around the exits and therefore leads to a longer evacuation time than the model proposed by the authors.

4.3.3.2 Classical mechanics Rincon et al. [21] draw their inspiration from Newtonian physics. The emotion of the agents is expressed in three dimensions using the PAD model. Emotion contagion is calculated seperately for each of the three PAD dimensions as the sum of the emotional attraction forces (F_r) of the senders on the receiver. The sender attracts the receiver based the emotional difference modified by the susceptibility of the sender (δ_r), defined as its empathy, the social affinity between the agents (α_{sr}) and the distance between the agents. The emotional acceleration in each dimension is (a_t) is derived using Newton's second law ($f = m \cdot a$), where the force is the nett attraction force (F_r) and the mass the reciprocal of the empathy of receiver. The emotional change in each dimension is expressed as the velocity (v_t) over time for each dimension, which is determined using the emotional acceleration (a_t).

$$F_r = \sum_{s \in N_r} \frac{\delta_r \alpha_{sr}}{2^{D_{sr}}} \cdot E_s - E_r \tag{34}$$

$$a_t = \delta_r * F_r \tag{35}$$

$$\Delta E_r = v_t * t = a_0 + a_t * t \tag{36}$$

The authors compare their model against the emotional evolution in a small group of participants recorded by an embodied agent that estimated the emotional state of the participants using a machine learning algorithm. The emotional state at the start of the experiment and the level of empathy of the participants, determined using a personality test, were used as input for the simulations. The authors conclude the model was capable of replicating the general patterns in the emotional development of the group and could in the future be used to aid the decision process in embodied agents when interacting with human groups.

4.3.3.3 Probabilistic Shao et al. [80] present a model aimed at simulating passengers at an airport that become angry following a service failure. First, whether contagion occurs between two agents at a timestep is determined by the chance the sender expresses emotion and the receiver to be susceptible to this emotion. The chance that the sender expresses its emotion (P_ε) depends on its expressivity (ε_s) and its relative dominance in the group (pos), where υ is a tuning parameter. The chance that the receiver takes up the emotion (P_δ) depends on its susceptibility characteristic (δ_r).

$$P_\varepsilon = \varepsilon_s \cdot pos - \left(1 - \varepsilon_s\right)\upsilon \tag{37}$$

$$P_\delta = \delta_r \tag{38}$$

When the sender expresses an emotion and the receiver is susceptible, the change in anger of the receiver is the difference between the average anger of the senders and the anger of the receiver, divided by the number of senders (n_r) and modulated by the average influence (W_r). The influence of a sender on the receiver (w_{sr}) is determined by the intimacy of the relation (I_{sr}) and the relative power coefficient (P_{sr}) of the sender over the receiver, where χ, ψ and ω are tuning parameters.

$$\Delta E_r = \frac{(A_r - E_r)}{n_r} W_r \tag{39}$$

$$W_r = \frac{1}{n} \sum_{s \in N_r} w_{sr} \tag{40}$$

$$w_{sr} = \chi\alpha\left(I_{sr}\psi\beta + P_{sr}\omega\gamma\right) \tag{41}$$

Shao et al. combine their contagion mechanism with a decision model based on a neuro-fuzzy logic network and the social force model for steering. They find that in the simulations with emotion contagion the reaction of the passengers to a flight delay is similar at first to those without emotion contagion. However, after a couple of hours the number of aggressive people in simulations with emotion contagion suddenly escalates, while the model without this takes a few hours more. In a third experiment two measures were implemented that prevented this escalation. Five staff members walked around appeasing the agents that were most upset with information and food, and five police agents deter the agents nearby from displaying aggressive behaviour. The authors conclude their model can realistically simulate the emotional development of travellers, but do not present validation against empirical data.

4.3.3.4 Threshold Bu and Yiyi [81] focus on events of mass aggression in crowds. They propose a model where contagion takes place when between agents that are emotionally similar. If the difference in emotion of an agent to its nearest neighbour is less than a global threshold, contagion takes place. Whether emotion increases or decreases depends on the emotion of the receiver (E_r). If this is equal or higher than 0.4, the emotional difference between the agents modulated by the susceptibility of the receiver (δ_r) and expressivity of the sender (ε_s) is added to the emotion of the receiver, otherwise it is subtracted.

$$\Delta E_r = \begin{cases} \delta_r \cdot \varepsilon_s \cdot \left|E_r - E_s\right| & E_r \geq 0.4 \\ -\delta_r \cdot \varepsilon_s \cdot \left|E_r - E_s\right| & else \end{cases} \tag{42}$$

The authors find that the model leads to polarization because the agents only exchange emotion with others that are similar and escalate their emotion further. This is further strengthened by spatial segregation because the behavioural response for positive agents in to leave while negative agents aggregate and vent their anger.

4.3.3.5 Other Ta et al. [82] present a contagion mechanism that is the most simple in this section. The contagion process depends only on one agent property, a fixed level of confidence of the receiver in the sender (α_{sr}). Considering only emotion contagion, the authors find that when the agents do not move, emotion contagion results in emotionally aligned clusters. When the agents walk around to random targets, the agents converge emotionally. Introducing an emotional input from the environment, specifically a fire, they find a dynamic pattern as the agents move closer and further from the fire.

$$\Delta E_r = \frac{1}{n} \sum_{s \in N_r} \alpha_{sr}(E_s - E_r) \tag{43}$$

5 Discussion

The first objective of the present literature review was to provide a structured overview of agent-based models of emotion contagion via a systematic approach. For this we have presented an overview of agent characteristics commonly found in models that consider emotion contagion. Further, we have introduced a system to categorize the diverse mechanisms of emotion contagion and examined the contagion mechanism and results of each included study. In this section we explore some overarching themes that came forth from the examination of the individual studies. With this discussion we aim to attain the second and third objective of this review, which are to evaluate the applications, performance and limitations of the contagion mechanisms and to identify directions for future research.

5.1 Evaluation

In the first category, that we termed ‘group statistic’, the emotional state of each agent is affected by a statistical measure of the emotional state of its neighbours. The relation between the receiving and the sending agent is not considered and all neighbours are treated equally. An advantage of this method is that it is relatively simple to compute and to understand emotion contagion, while it was shown to produce a variety of patterns also reported for real crowds. On the other hand, this method cannot capture the full effects of personality, distance and social relationships among people. This may explain why it is least often used in the studies examined in this review.

The second category, called ‘epidemiological’, emotion contagion only occurs from an emotionally infected agent, towards an individual in a susceptible state, which could be seen as having no strong emotion. This is different from the other categories where contagion is a continuous process in which all agents can potentially influence each other. The hypothesis that underlies the epidemiological approach is that the emotional state of a person is affected by that of another person only if this person has clear emotional expression, while a lower emotional state does not affect the emotions of others. The categorical nature makes epidemiological models especially suitable to simulate scenarios where there is a clear difference in emotional states, that can flip like the change from calm to panic. Therefore, it is not surprizing that we found most epidemiological-based studies simulate scenarios in which strong emotions spread through a crowd, like evacuations and riots. Of all examined studies, most used an epidemiological-based method of emotion contagion, possibly because most work currently focusses on evacuations and mass aggression, motivated by the severe personal and societal consequences that an unregulated spread of emotions can have in these scenarios.

The third category, called ‘dyadic relations’, consists of models where emotion contagion is defined as an emotional exchange that occurs on a continuous scale between two people, and is affected by the connection and properties of these people. These models assume all levels of emotion are expressed to varying degrees and contagion occurs constantly, including when the level of emotion is very low. If it is correct that also faint emotions are expressed and decoded in crowds, the continuous nature of dyadic-relations-based mechanisms makes them theoretically more suitable than epidemiological mechanisms to simulate more subtle forms of emotion contagion. An example of this might be a slow change in atmosphere at a bar. A drawback is the extra computation that is required to calculate contagion among all agents instead of a subset. Also when comparing the most prominent models of both categories, Tsai et al. [46] and Xu et al. [61] remark that the number of parameters of the dyadic-relations-based ASCRIBE model [49] is significantly larger than the epidemiological-based Durupinar model [71], making it more difficult to automatically tune its parameters.

Looking at Tables 4, 5 and 6, there are four studies that compared models across categories directly. Mao et al. [79] compared their model (dyadic relations) to that by Cao et al. [62] (epidemiological) and Tsai et al. [46] (group statistic). However, because the implementation of these models also differed on other points than the contagion mechanism, like the behaviour model and the inclusion of social relationships, the results are not informative in evaluating the contagion mechanism. Liu et al. [50] compare their model (group statistic) to that of Durupinar (epidemiological) in an evacuation setting. They find that contagion in their model takes more time than in the Durupinar model, but conclude this is likely due to differences in the perception model, not the contagion mechanism. Tsai et al. [46] compared their ESCAPES model (group statistic) which they described as a baseline to the ASCRIBE model by Bosse et al. (dyadic relations) and the model by Durupinar et al. (epidemiological). They found that the simulations with the ASCRIBE model most closely resembled the trajectories of people in several videos of evacuations. Durupinar et al. [40] however responded that two aspects of their model were misinterpreted when their model was integrated in the ESCAPES environment and are likely to have affected the outcome of this comparison. Lastly Xu et al. [61] compare the ASCRIBE model with multiple emotions (dyadic relations) as presented by Neto et al. [72] against the model by Durupinar et al. [40] (epidemiological). They measure several individual and group-based metrics to score the similarity of the simulations against video of real evacuations and find that the models perform comparably. We conclude that based on these comparative studies no clear conclusions can be drawn about the performance of the broad categories of contagion mechanisms, despite fundamental differences in the approach.

5.2 Contagion in a multi-emotional environment

While simulating only panic or anger may be enough to accurately simulate some scenarios like evacuations, most everyday scenarios will contain many types of emotion that affect the behaviour of the crowd. We found several studies have modelled the contagion of multiple categorical emotions (like anger, joy and boredom). However, the contagion of multiple categorical emotions in a quantitative way was reported to pose challenges, irrespective of the type of contagion mechanism. When the emotional state of an agent consists of multiple emotions it is not evident which emotion(s) should impact the contagion process and behaviour of the agent. What does it for example mean that an agent is mostly happy but also a little bored and sad? Xu et al. [54] proposed two opposite emotions that are inversely related to each other, yet with the three emotions in the example the reduction to a single number is difficult as bored and happy are not opposites of each other. Another problem noted by Aydt et al. [53] is that it seems unrealistic that an agent for example becomes strongly happy and bored at the same time. One solution to these challenges is to selected the emotion with the highest value as the only relevant emotion. However, Durupinar et al. [40] found that this approach can result in rapid fluctuations between strong emotions leading to erratic behaviour and oscillations that do not seem realistic. They proposed a model that included the dimensional Pleasure-Arousal-Dominance model of emotion as an extra layer that represents the average emotional state of the agent. Thereby it functions as an intermediary between the categorical emotions on one side and emotion contagion and behaviour on the other side.

A simpler solution may be to only simulate the contagion of continuous emotions. We found two existing agent-based models that include the contagion of continuous emotions [21, 78], but neither performs simulations of emotion contagion in a large crowd distributed in space. Therefore, we have recently proposed an extension of the ASCRIBE model that simulates the contagion of the continuous emotions valence and arousal among supporters in a stadium [83]. In this model, valence and arousal spread independently, but together form a single emotional state of an agent as a point location in the valence-arousal space, preventing confusion about which emotion impacts emotion contagion and behaviour. While the model is not empirically validated at the time of writing, preliminary results showed that this contagion mechanism could produce an emotionally dynamic but stable system, in which the emotions of agents made sensible transitions. A potential disadvantage of the contagion of continuous emotions is the mapping that is required to translate specific areas in the emotion space to categorical labels of emotion that are typically used in society. As far as we are aware, currently there is no consensus on such a mapping.

5.3 Validation and empirical data

The concept of contagious emotions has been studied for a long-time in social sciences, yet the use of emotional components in agent-based models of crowd behaviour is relatively recent. Adding an emotional component to agents is often touted to increase the likeness to behaviour of real people, especially during stressful situations [20], but to justify the application of such models in society empirical validation is required. Models inherently simplify reality, including some aspects while leaving out others. Validation of a computational model often consists of measuring real phenomena and testing whether a simulation can reproduce these measures sufficiently. The assumption is that if the patterns of real events are accurately predicted by the simulation, the underlying model is valid.

Kefalas and Sakellariou [84] argue against the use of the term validity for multi-agent simulations that involve emotion contagion as the requirements for this cannot be met due to the numerous factors that influence the emotional state of a person. They argue currently no complete model of emotion exists and that it is not a realistic prospect to obtain the complete data of what occurred during an event as well as the full initial state and historical context of individuals in a crowd. Instead, they propose that studies modelling emotion contagion in crowds should aim for ‘believability’ instead of validity. In place of the model being able to precisely reproduce a specific event, such as the exact evacuation times, the model merely should produce characteristics that are in a statistically sense highly similar to what may happen in such events. This approach however currently lacks a shared definition for believability and the indicators to measure whether an emotional crowd is simulated ‘believably’. While obtaining ecological validity may indeed currently not be feasible in the context of emotional crowds, there are other forms of validity that can be considered like criterium validity, construct validity and content validity [85, 86].

Based on the reviewed papers, validation of models of emotion contagion currently is not approached in a uniform way. One form of content validation that was used in five studies simulating emergency situations [53, 61, 65, 70, 87] is that of face validity. Typically, these authors showed the visual output of simulations and video of real incidents to people, or let people interact with the model in the form of a serious game. The participants then were asked about the performance of the model, for example how realistic it seemed. In all five cases, these people were not experts in the respective field. Therefore, these attempts can merely provide face validity, a basic form of validation that tests whether the instruments at first glance shows what it is designed to show. More valuable would be to test for another form of content validation called expert validation. Involving professionals, such as security personnel, to judge the model may provide an alternative way to establish validity of models that include emotion contagion in crowds. Requisite is that emotion contagion leads to clearly perceivable differences in the application scenario.

Further, as shown in Tables 4, 5 and 6, we found that 10 of the 34 included studies (29%) have tested criterium validity using data of real crowds. Half of these studies date from the last two years. Most data-based validation attempts used video of real crowds, often of incidents that involved an evacuation or mass aggression. In these studies, the authors measure the behaviour of the people that are filmed. These involve group measures like the average evacuation time, entropy and group direction, as well as individual-based measures like their trajectory. Others have used heart-rate data and surveys as a more direct measures for the emotional development of people. The authors compare these measures in simulations with and without emotion contagion to those of real people, where a closer match of the simulations that include emotion contagion is presented as an argument for construct validity. Nevertheless, while the simulations with emotion contagion often perform closer to real crowds than without emotion contagion, most studies found the simulations differed significantly from the behaviour of real people at the individual-level. An explanation that is frequently given for this is that the individual characteristics of the people in the video are not known, preventing the setting of a correct starting state in the model. A possible solution to this problem comes from advances in automated methods to automatically and reliably collect affective information. While still in an early phase, machine learning techniques to recognize emotional expressions from faces, posture, speech and biometrical data have gained much attention in recent years and may in the future allow for detailed tracking of the emotional state of members in the crowd [88].

However, obtaining data in the wild is bound by limitations due to privacy and individual consent, especially as these data include highly personal information. An alternative is to retrieve experimental data, by orchestrating a crowd of participants that can give consent. While this seems a promising route to obtain high-quality data about the emotional development of a crowd, it poses an immediate challenge. Most of the examined studies are focused on scenarios with extreme levels of emotion, motivated by a strong incentive to prevent these situations as they result in high personal and societal costs. Yet, exposing participants to these situations would pose an unacceptable risk to their safety. Further, if the participants are aware that they are recorded and that there is no real personal danger during the experiment, their behavioural and emotional response may be different from natural situations. Still, after a decade of large theoretical development, advances in empirical evidence are needed to determine to what degree the models can predict the behaviour of emotional crowds under different circumstances to come to practical applications. Though challenging, future research should first aim to establish a clear and shared methodology for validating models of emotion contagion in groups, for which might be drawn upon experience of research involving emotion contagion in social sciences. Second, we recommend that future work focuses on the collection of high-quality data of emotional development in small groups in an experimental setting, to determine the validity of models of emotion contagion at a more fundamental level. This would allow to control for other factors like other emotional stimuli, social relations and personality, via careful experiment design and the use of questionnaires. This way a start can be made to determine minimal models that are adequate to simulate specific types of crowds and ultimately justify their application in society.

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