A landscape of crowd-management support: an integrative approach

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Abstract

Of the many crowd behavior models, very few have been used in assisting crowd management practice. This lack of usage is partly due to crowd management involving a diversity of situations that require competencies in observing, sense-making, anticipating and acting. Crowd research is similarly scattered across disciplines and needs integration to advance the field towards supporting practice. To address these needs, we present INCROWD, an integrated framework detailing a high-level architecture of a decision-support system for crowd management and model development. It also offers a lens for categorizing crowd literature, allowing us to present a structured literature review.

Keywords: crowd management, crowd modeling, decision-support systems, system architecture

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1. Introduction

The importance of understanding human behavior in crowds is undisputed. It is required for ensuring that proper support can be given to crowd managers in preparation and during a crowd event. The last decades proposals have been put forward to capture the idiosyncrasies of crowd behavior in a variety of ways to understand (parts of) crowds. These understandings or models come in different forms, ranging from extremely formal (e.g. computational models) or implicit knowledge (e.g. mental models of experts). The crowd models that are grounded in science originate from very different disciplines and practices, including psychology, sociology, theoretical physics, applied mathematics, artificial intelligence, and computer science. Despite having helped researchers better understand crowd behavior, there are only few examples where these models have actually been used to assist in crowd management (with some exceptions, including e.g. [Ball, 2007]). There is thus a substantial gap between crowd research and crowd management practice.

Crowd management practice involves accessing and interpreting a wide variety of information sources, predicting crowd behavior as well as deciding on the use of a range of possible, highly context-dependent intervention mechanisms. In the context of this paper, decision-support for crowd managers denotes any computer-assisted support on each of these tasks. Both crowd research and crowd management practice have developed and improved tremendously in their attention for preparing crowd events. Automated tools are increasingly being offered for particular aspects of crowd management, but much more is needed [Challenger et al., 2009b].

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We argue that the lack of adequate decision-support is partly due to the status of the majority of current crowd models. Firstly, most models are not ready for use: they are (if at all) tested for acceptability in science, but not for usability in practice. Secondly, most models reflect a particular discipline and thus target only one specific element of crowd management, i.e. acting, observing, interpreting, predicting and deciding. To truly provide decision support for crowd management, a new approach is needed that integrates data gathering, assessment and prediction of crowd situations, and evaluating decisions regarding interventions. Crowd research has the potential to support crowd management in a better way by taking an integrated view in the development of models that are operationally usable. This would allow crowd management to benefit from the wide variety of existing knowledge and tools (models) regardless of the different (disciplinary) forms in which they appear. This can be achieved, for example, by connecting and using both expert insight and social theory to predict the further development of a crowd while being fed information from a pattern detection algorithm to interpret data from cameras at a crowd site.

In particular, we see potential for improving support *during* an event, i.e. in real-time. In our view, we should make use of the strengths of both humans and technology. Human expertise and experience remains unbeaten in rapidly assessing (complex) situations. Technology on the other hand, can rapidly acquire, process and digest large amounts of information, which, in our view, is under-exploited. We perceive integrated semi-automatic decision-support as *the* next step in increasing the safety and success of crowd events.

In this paper we aim to give guidance towards integrated crowd management support by providing a decision-support framework INCROWD. INCROWD is an integrated framework for crowd interaction (actuating and sensing), mining, predicting, and making decisions to manage the behavior in a crowd, relating to the diverse practices of crowd management (observing, interpreting, predicting, decision-making). The framework functions as an architecture for a decision-support system for crowd management as well as model development framework towards operational support. Moreover, in this paper the INCROWD framework is also used for identifying areas in need of more research by classifying existing literature on crowd-behavior understanding and management, simultaneously allowing us to substantiate our claim that an integrative approach is needed.

We organize this paper by first providing an overview of crowd research as communicated in other review papers. We continue by looking at how crowd management is practiced today in section 2. In section 3 we discuss the means of operational support for crowd management, concentrating on the core elements of our framework and illustrating how operations can be supported in real-time, i.e., *operations engineering*. In section 5 we focus on the importance of supporting model development and show that model development and operational crowd management are actually closely related. The framework then allows us to provide a status report on the status of the current literature in section 6, where we assess and categorize 237 papers. Finally, we come to our conclusions in section 7.

1.1. Background: existing reviews

Numerous review papers on understanding crowd behavior are available in the literature. For instance, Reicher [2001] and Challenger et al. [2009b] provide a (historical) overview including different schools of thought in the psychology of crowds (theoretical models). Bryan [1999] studies the maturity of human behavior in the context of fire. Others consider state-of-the-art techniques, such as the development of intelligent distributed surveillance systems and image processing technologies [Valera and Velastin, 2005], recognition and wearable sensors [Atallah and Yang, 2009] or advocate a particular type of crowd modelling [Hughes, 2003]. A majority of these review papers addresses emergency evacuation, either to highlight the importance of taking a more integrative approach of the relevant connected research fields [Santos and Aguirre, 2004; Sime, 1995; Venuti and Bruno, 2009], to reflect on existing guidelines for facility design [Stanton and Wanless, 1995], or to provide insights into the most often used methods of modelling [Gwynne et al., 1999; Alsnih and Stopher, 2004].

Each review paper targets its own (disciplinary) crowd niche, the exception being the report of Challenger et al. [2009b] that covers a range of mathematical models, theoretical crowd-behavior models and crowd-simulation tools (i.e., predicting techniques), but also a wealth of information regarding crowd behaviors, characteristics, and typologies. Moreover, the report provides an extensive list of guidelines for crowd management and emergency situations, and identifies challenges in crowd management as well as existing gaps and makes recommendations for future crowd research. Despite its broader view, the focus lies on the prediction aspect of crowd management. This reflects a general tendency of these review papers focusing on only one or, at the most, two aspects of crowd management. Bellomo and Dogbe [2011]; Duives et al. [2013]; Challenger et al. [2009b]; Venuti and Bruno [2009] and Alsnih and Stopher [2004], for instance, solely focus on predicting models or techniques. Bellomo and Dogbe [2011] present a review and critical analysis of existing mathematical models of vehicular traffic and crowd phenomena, addressing different representation scales (i.e., microscopic, macroscopic, and statistical) and the corresponding mathematical structures. The authors critically analyse the presented models, discuss their limitations and focus on the identification of new research perspectives which concern both modeling and analytic issues. Moreover, they include a review of the empirical data that is used to design and validate models. Similarly, Duives et al. [2013] provide an overview of a range of crowd simulation models and assess these models regarding their precision in simulating known crowd phenomena and their computational load. Their assessment shows that the models can be roughly divided into two groups: (1) computationally expensive, but highly precise microscopic models, and (2) computationally inexpensive, but inaccurate macroscopic models. Their review concludes that since practical applications actually require both precision and efficiency, e.g. real-time decision-support for crowd management, the current pedestrian simulation models are inadequate.

While the above review papers focus solely on predictive models, others solely focus on the mining aspect. For instance, the review presented in Valera and Velastin [2005] describes the state of development of intelligent distributed surveillance systems, including a review of current image processing techniques that are used in different modules as part of the surveillance systems. Surveillance activities addressed involve the recognition of humans and objects as well as the description of their actions and interactions. Areas for further research are also identified. These include data fusion and tracking methods in a cooperative multi-sensor environment. Their review focuses on techniques for mining crowd data stemming from visual sensors (e.g. video cameras), which so far have been the most prevalent type of sensors used in crowd monitoring. Other reviews focus on two distinct aspects of crowd management [Zhan et al., 2008; Atallah and Yang, 2009; Santos and Aguirre, 2004; Alsnih and Stopher, 2004; Gwynne et al., 1999]. For instance, Zhan et al. [2008] present a review of crowd-analysis methods employed in computer vision, including methods for automatic crowd-feature extraction to provide crowd-density measurement, object recognition and object tracking. The review thus focuses on mining and prediction techniques. Moreover, the paper presents a review of computational crowd models, classifying them into physics-inspired, agent-based, cellular-automata and nature-based models. The paper also presents several approaches that combine computational crowd models with vision-based techniques, pointing out that it is possible to develop intelligent systems that combine these approaches. Atallah and Yang [2009] present a review on the use of pervasive sensing for understanding human activities in general (and not only crowd behavior). The focus of their review lies on sensing and mining techniques targeted at measuring, recognizing and understanding human behavior. Their review includes current work on activity recognition based on a vast range of ambient and wearable sensors, as well as methods for modelling human behavior, such as probabilistic models and approaches for anomaly detection. Moreover, challenges and new research opportunities are discussed, which include incorporating temporal information in behavior modeling and unsupervised anomaly detection.

In existing reviews on understanding crowd behavior, the aspects of sensing, mining, and predicting are commonly, yet separately, covered, whereas the practice of decision-making, e.g. which interventions are effective, is generally addressed to a lesser extent beyond stressing the importance of a particular study.

In our present review we aim at providing an overview of all aspects of crowd management by giving an overview of the work done in each of these stages and notably how they are connected. Multiple reviews highlight the need for a more multidisciplinary scientific approach, i.e., adopting the often ignored insights from social psychology, e.g. [Santos and Aguirre, 2004; Sime, 1995]. Although we second this need wholeheartedly, we stress that this needs to be carried out in a problem-driven, not discipline-driven integrative approach. We look at crowd management as a whole and thus adopt an integrative approach involving actuating and sensing (crowd interaction), mining, predicting, and decision-making, which is formalized by means of the INCROWD framework.

2. How crowd management is currently performed

When looking at the wealth of information available on crowd management (see, for example, [Challenger et al., 2009b; Health and Executive, 2000; Martella et al., 2013]), a majority concentrates on the preparation for potential or expected situations or events. We refer to this phase of crowd management as the "event preparation" phase. During an event, crowd management goes through an "event execution" phase, for which the available literature focuses mostly on the *monitoring* of the crowd. The crucial processes of situation assessment and decision-making are however treated superficially in the literature.

In this section, we give an overview of how management of crowds is currently planned and executed, including the processes of situation assessment and decision-making. Much of the information we present is based on [Challenger et al., 2009c,a; Health and Executive, 2000; Martella et al., 2013], as well as work on decision-making in complex, uncertain, and highly dynamic situations [Klein, 1999]. Furthermore, we indicate existing approaches and technologies from the literature that are relevant to crowd management at its various stages.

2.1. The event preparation phase

Crowd management typically refers to the systematic planning, and providing guidance for the safe and orderly development of events where large numbers of people come together. Event preparation thus focuses on planning, which is considered to be the largest part of efforts in crowd management [Martella et al., 2013]. Planning typically involves anticipating what might happen regarding a crowd in a given context and preparing for it. As such, preparation includes designing for the desired behavior of the crowd, but also foreseeing potential issues and devising contingency and emergency plans to deal with them [Health and Executive, 2000, p. 33]. The resulting plan usually targets the site design, a supporting technical infrastructure, a number of assigned personnel, and prescribed operational interventions for dealing with 'normal' as well as anticipated critical situations [Health and Executive, 2000, p. 27], [Challenger et al., 2009c, p. 13], [Challenger et al., 2009a, p. 250], [Martella et al., 2013]. The quality of the anticipatory analysis in combination with the effectiveness of the planned or operationalized measures are particularly critical to effective crowd management. Automated support for *what-if* analyses can play a crucial role.

Planning is typically carried out in a team using a multidisciplinary approach that draws on the perspectives and expertise of a wide range of individuals. These include the event organizers, crowd managers, police, stewards, first-aid representatives, local authorities, transportation operators, and crowd simulation experts, etc. [Challenger et al., 2009c, p. 71], [Challenger et al., 2009a, p. 260], [Health and

Executive, 2000, p. 7]. These highly multidisciplinary efforts required for planning a crowd event may partially explain why it is so difficult to provide an adequate decision-support system.

Planning involves a wide range of activities, addressing, among others, the critical moments when people enter and/or exit the event site, their activities and movements within and around the site. Also, strategies for improving flows and preventing densities from reaching critical values at any given location and time need to be taken into account [Health and Executive, 2000, p. 7], [Martella et al., 2013]. The literature points out several approaches regarding the improvement of crowd flows [Challenger et al., 2009c, p. 74]. These include the use of separate doors for entry and exit [Helbing et al., 2002], placing obstacles to encourage lane formation [Helbing et al., 2002], ensuring that entry and exit points are wide enough to accommodate groups of people to pass through [Pan et al., 2007], and making line-of-sight paths as long as possible to allow individuals to see their destination and choose the most direct route [Davies et al., 1995]. Advanced 3D simulations are increasingly used to assist the experts in planning [Van Toll et al., 2012].

These approaches represent universally applicable interventions for crowds and should be relatively easy to integrate into a simulation environment for planning crowd events. However, crowd management also requires the consideration of aspects that are not easily formalized into a simulation environment. For example, the purpose of a crowd event, the profiles of visitors, visitor's knowledge of and experience with the event, the characteristics of the event site, the effect of the weather, etc. [Challenger et al., 2009c, p. 133], [Health and Executive, 2000, p. 7], [Martella et al., 2013].

Another important part of crowd planning is risk assessment. In order to identify risks, a common approach involves the generation of possible *what-if* scenarios regarding event disruptions and emergencies [Health and Executive, 2000, p. 19]. An automated example is the work by Schubert and Suzic [2007] who introduce assistance by means of an evolutionary algorithm that selects interventions for a given scenario. Nevertheless, devising courses of action for dealing with a given situation typically relies solely on expert knowledge.

2.2. The event execution phase

During the event, the situation in a crowd must be continuously monitored, assessed, and appropriate actions (typically according to the original plan) need to be selected and implemented. In all these processes, communication is a key element [Challenger et al., 2009a, p. 263]. This includes both communication among crowd management team members as well as communication between the crowd management team and the crowd itself. A solid command and control structure must also be in place, with a central control point responsible for the overall event management across multiple locations [Challenger et al., 2009a, p. 269].

During the event, crowd observation and monitoring enables the assessment of a situation and the detection of potential problems at an early stage, ultimately allowing the selection of appropriate action. The most common monitoring strategy for large crowds uses stewards and officers on the ground near or inside a crowd, as well as surveillance cameras whose output is watched by (human) agents in a control room [Martella et al., 2013]. Information that is typically monitored includes counts of people in a small identifiable area, the space between people, the rate of flow into or out of an area, the overall number and distribution of people in the crowd, the general crowd mood, signs of distress, pushing or surging, indications of bad temper or excitement as well as any signs of other potential crowd problems [Health and Executive, 2000, p. 47]. To what extent such observations can be carried out in an (semi-)automated fashion is subject to research as addressed in this paper.

Other monitoring systems and strategies include the deployment of helicopters and Unmanned Aerial Vehicles equipped with video cameras, turnstiles linked to automatic counting systems as well as scanning social media for the usage of certain keywords [Martella et al., 2013]. As monitoring information becomes available, experienced stewards and officers combine and interpret the information in real-time and translate it—by means of mental models—into a higher-level assessment of the crowd situation: a state of situational awareness [Klein, 1999]. Therefore, it is crucial that personnel with extensive experience in understanding and managing crowds (hereinafter referred to as "crowd experts") are involved in these assessments [Challenger et al., 2009a, p. 268], [Klein, 1999]. On a higher abstraction level, a situation in a crowd may be classified according to, for example, known crowd behaviors and patterns, or assessed as a normal, abnormal, dangerous, or emergency situation. Moreover, once a certain situation has been detected, crowd experts anticipate resulting events [Klein, 1999]. Here lie considerable challenges if the goal is to support, enhance or even replace the human experts by automated means.

As indicated, the use of technology and automation in the process described above is still limited. The processing of video data by means of video-analysis algorithms [Davies et al., 1995] is performed automatically in some simpler cases (e.g. when having relatively low densities) to provide counting, density, and flow estimations for crowd management [Martella et al., 2013]. However, these algorithms do not address emotional and psychological aspects of the individuals in a crowd. Insights into these aspects may be obtained in an automated fashion by mining social media [Martella et al., 2013] as well as automated self-reporting applications [Li et al., 2014]. Regarding high-level assessments and interpretations of a crowd situation, a number of algorithms have been proposed. Examples include classification into 'normal' and 'abnormal' behaviors, mostly based on video data[Rodriguez et al., 2011; Mahadevan et al., 2010; Mehran et al., 2009; Pathan et al., 2010], but also based on multiple sensors[Andersson et al., 2009; Drews et al., 2010]. The recognition of crowd-behavioral patterns [Roggen et al., 2011] and the unveiling of social-network structures [Isella et al., 2011] based on on-body sensor data have also been addressed. Of these types of approaches, none have been reported to be used in real-time crowd management [Martella et al., 2013; Challenger et al., 2009b], possibly due to performance issues and due to limitations with regard to the situations that these solutions can address. Finally, currently available monitoring and assessment technologies are also limited in that they can provide only real-time interpretations of a situation, but not predictions, due to the apparent lack of *appropriate* models. Predictive models have been proposed in abundance, as we discuss in this paper, but their use in real-time crowd management is lacking.

Achieving situation awareness is key in any process of decision-making, most notably in complex, uncertain, and highly dynamic situations [Klein, 1999; Osinga, 2007]. For crowd experts, the awareness of the current situation allows for selecting a matching scenario and an appropriate course of action. In case the current situation does not satisfactorily match any of the prepared scenarios, expert knowledge needs to be brought in to modify selected actions or devise completely new ones from scratch [Martella et al., 2013]. The scenario-based approach described in [Schubert and Suzic, 2007], in contrast, automates the decision-making process by representing scenarios (as well as the current situation) in a computer-understandable format. The proposed representation is, however, quite simplistic and does not allow for the representation of complex scenarios as found in typical crowd situations.

Finally, once a course of action has been selected, the actual action takes place and its consequences must again be monitored to evaluate whether it had the desired effect. In fact, the processes of monitoring, interpreting, predicting, deciding as well as acting takes place continuously. They are part of a continuous decision cycle which, according to [Osinga, 2007], all intelligent organisms and organizations undergo. The crowd situation may of course change while these processes are taking place, therefore it may be necessary to change or cancel planned actions to accommodate such changes.

2.3. Beyond preparation - a focus on real-time support

There is no doubt that preparation is key in crowd management. At the same time, the processes that occur in *real-time* are just as crucial. Particularly, support in decision-making would be a major contribution. Therefore, in this paper we focus our attention on real-time processes of crowd management: *situation monitoring*, *interpretation* and *prediction* as well as *decision-making*. Our focus does not exclude the use of the framework for preparation purposes through predicting expected scenarios. Furthermore, we focus on the processes that are relevant for decision support, i.e., those leading to a decision, but not on the implementation of the decision itself. We adopt an integrative approach towards real-time crowd management support which clearly reflects and describes decision-making in complex and dynamic situations [Klein, 1999; Challenger et al., 2009c,a; Osinga, 2007].

3. INCROWD

We now turn to detailing our framework, called INCROWD which we use for two purposes: First, our framework can be seen as a proposal for organizing decision-support systems for crowd management, and thereby represents an architecture for such systems. We deliberately incorporate the human expert into our framework, since they are, and possibly will remain, the providers of the most adequate (mental) models used in crowd management. Second, INCROWD provides a basis for identifying various elements that are needed to support crowd management. In other words, it is problem-driven and opens connections to relevant knowledge, methods, and techniques in other fields relevant to crowd management. By subsequently classifying existing research in the context of INCROWD, we arrive at a proposal for a research agenda in section 6.

3.1. Overview

At a high level, INCROWD consists of four major subsystems, as shown in Figure 1.

- The **crowd-interaction subsystem** provides the interface between the actual crowd and (real-time) support systems for crowd management. We distinguish two types of interfaces. **Actuators** are used to intervene in a crowd. Typical examples of actuators are mobile barriers, traffic lights, displays, and tailor-made smartphone applications. **Sensors** are used for measuring, or sensing the state of a crowd, and typically include cameras and microphones, but also smartphones and social media.

- The **mining subsystem** is responsible for interpreting the raw data that captures the state of a crowd. Typically, it deploys many data-mining techniques and various methods for crowd analytics, along with interpretations provided by human experts.

- The **predicting subsystem** is responsible for predicting the state of a crowd. It typically contains predictive simulation models, but also models for generating synthetic data sets that are subsequently fed into the mining subsystem for further analysis. Practice shows, however, that human expert knowledge provides a significant contribution to predicting future crowd states.

- Finally, the **decision-making subsystem** encapsulates the methods and techniques for arriving at a decision regarding adequate crowd intervention. It involves selecting or generating an intervention, which is then implemented by using the actuators available in the crowd-interaction subsystem. The actual implementation of a decision in crowd management lies beyond the scope of decision-support (and thus of this paper).

We further draw a distinction between **computational** and **noncomputational instruments** for crowd management support, visualized as black and grey elements in Figure 1. Computational instruments can, in principle, be executed in a fully automated, mechanized fashion. Noncomputational instruments do

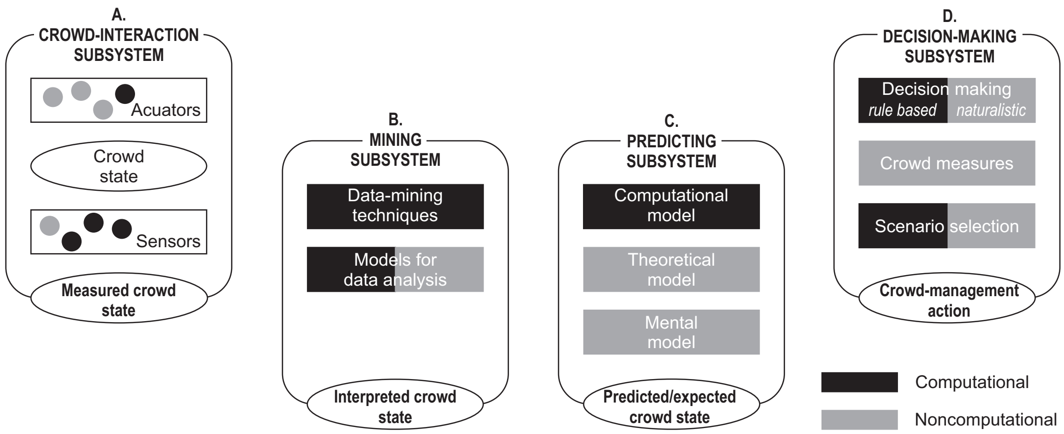

Figure 1: The four major components of INCROWD.

Table 1: Examples of instruments available for crowd management.

	Crowd interaction		Mining	Predicting	Decision-making
	Sensing	Actuating			
Computational	Simple data, collected by digital sensor or a human, that can be directly fed into a computer.	Feedback through smartphones, billboards, traffic lights, fully computer-controlled.	Standard data-mining techniques	Model-based computer simulations	Analytical decision-making strategies, e.g. Multi-Criteria Decision Analysis (MCDA) [Figueira et al., 2005; Anonymous, 2009]
Noncomputational	Advanced data, purposefully designed questionnaires or observations by humans: visual, auditory	Intervention by security officers, manually controlled traffic lights, mobile barriers	Mental analyses (experience based), e.g. a sense that something is going on given observations.	Theoretical or mental analysis, e.g. a (social science) theory or mental simulations such as scenario thinking to predict	Naturalistic decision-making strategies, e.g., the Recognition-Primed Decision (RPD) model [Klein, 1989]

not act automatically, either because that is (still) impossible or impractical. The distinction is important since effective crowd management cannot solely rely on automated means: it requires input from both human experts and noncomputational knowledge. Recognizing which parts of a decision-support system cannot (or should not) be automated is key for its design. Examples of computational and noncomputational crowd management instruments are shown in Table 1, which considers the four major components in INCROWD.

3.2. Continual example: Large-scale outdoor event in the city of Arnhem

In order to illustrate our framework and its components, we use a continual example of a crowd in a large-scale outdoor event. As a representative example we choose the World Living Statues Festival, an annual event in the city of Arnhem (The Netherlands) where over 200 live statues attract more than 300,000 visitors. Arnhem is situated in the Eastern part of the Netherlands, with a population of 150,000 and a dense downtown area covering only a few square miles (where the festival is located). Managing the expected crowd is essential for reaching the goals of the event organizers (e.g., enjoyment, safety, public order). The existing crowd management in this example uses various methods, including a combination of computational and noncomputational approaches.

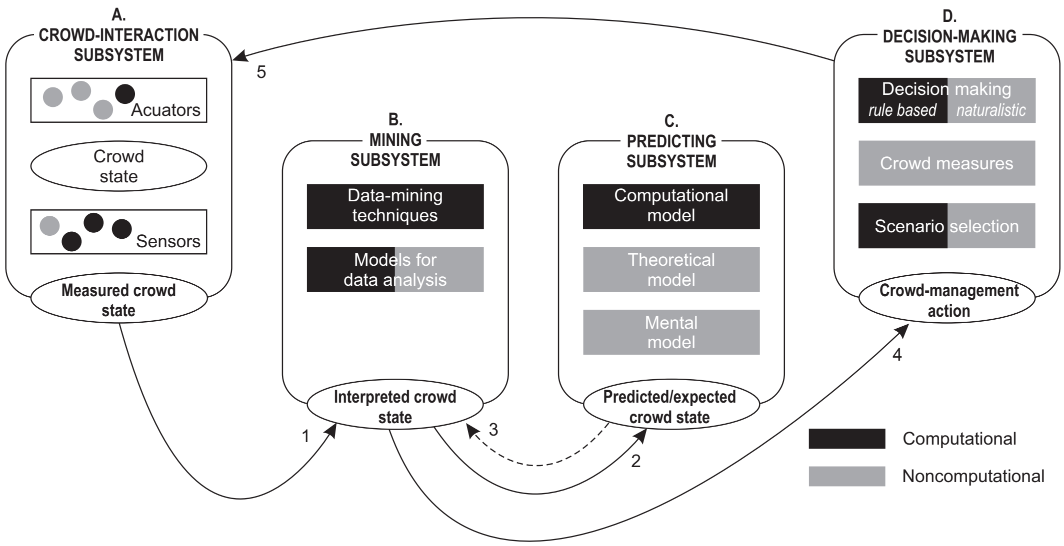

Figure 2: The overall flow associated with the iterative process of crowd management.

The crowd is observed with some 80 video cameras at various locations in the festival site. In addition, approximately 50 Wi-Fi hotspots are deployed to detect smartphones (as anonymized data). These detections provide additional data on the whereabouts of crowd members: how fast people are moving through the area, what their general trajectories are, what the estimated crowd densities are, to name but a few. Security officers walk around and act as observers, regulate the streams of visitors, and intervene in various ways where deemed necessary. Observation data is gathered in a control room where operational managers observe the video streams and other incoming data, and where automated tools estimate the amount of people and densities at various locations, along with other spatio-temporal metrics. Security officers within the crowd send in their reports, again in various forms: through special smartphone applications, but also by more traditional means like calls to the control room.

Based on what is visually seen, detected from hotspots, communicated on-site, own personal experiences, and information automatically computed and retrieved by the decision-support system, the control room can direct cameras to points of attention and direct mobile teams of security officers to certain locations. Having identified a specific situation, be it potentially dangerous or otherwise, a crowd manager may need to decide on an intervention. Automated support is provided in the form of automatically deduced scenarios, together with interventions that are most appropriate for each scenario. A crowd manager will try to select the scenario that best matches the current situation and then select the corresponding cataloged intervention.

4. Operational support with INCROWD

INCROWD's four subsystems together provide the basis for a crowd management support system. By measuring the state of a crowd, correctly interpreting that state, and being able to predict the effects of an (non-)intervention, a crowd manager is able to use an implementation of INCROWD as an instrument to *manage* a crowd, as reflected in Figure 2. Crowd management in light of INCROWD reflects the integration of many different models. The aim of this framework is to allow crowd managers to *effectively* manage the behavior of crowd members regarding the aspects considered relevant.

The overall flow of crowd management is as follows. INCROWD collects information on the state of a crowd in the form of a continuous stream of (heterogeneous and potentially complex and/or conflicting) raw data. This data stream is fed into the mining subsystem that provides crowd managers with a meaningful interpretation of unfolding events (arrow 1). Using either the raw crowd data or its interpreted state, the prediction subsystem is ideally capable of predicting what may happen in the near future (arrows 2 and 3, respectively). Typically, the interpreted state (arrow 4) is used for selecting scenarios as well as making suggestions for crowd interventions in the decision-making subsystem, which can then be applied to the crowd (arrow 5).

We envision this system as a continuous loop that may include an evaluation of the effects of interventions as well as an evaluation of the mining and predictive models in the framework. Models are thus expected to be learned and improved in operation as increasingly more experience is gained. Here we enter the grey area between operations engineering and model development. For reasons of comprehensibility we keep them strictly separated and will discuss model development in the next section. We will now elaborate in more detail on the operational use of the framework for each subsystem.

4.1. Operational: Crowd interaction subsystem – Sensing and Actuating

As mentioned above, the crowd interaction subsystem represents the interface between support tools and the actual crowd. The interaction includes both actuating (intervening in a crowd) and sensing (measuring a crowd state).

From an abstract point of view, the state of a crowd can be represented by a collection of **state variables**. Typical state variables include:

- **spatio-temporal variables**: density, size, position, movement, and acceleration of (parts) of the crowd.
- **social variables**: purpose, age distribution, gender distribution, group membership, social structure, leadership, status, and social identity.
- **psychological-cognitive variables**: mood, mindset, intentions, and beliefs.

There are at least three independent problems with measuring the state of a crowd. First and foremost, there is definitely a modelling and representation issue, as what exactly comprises the state of a crowd is difficult to decide. The result is that often a semantically rich and potentially large dataset is acquired which is expected to capture what crowd managers are looking for. This dataset then needs to be further analyzed. Indeed, it is often unknown in advance whether certain data elements are relevant at all.

Second, a state variable σ may be complex, in the sense that it is a composition of other, simpler variables $\sigma_1, \sigma_2, \ldots, \sigma_n$. Both, the exact composition, and each constituent element σ_k may be (partially) unknown, nor is their potential interaction clear. Psychological-cognitive variables such as the ones mentioned above are examples of complex state variables.

Third, even if a state variable is well understood, as is the case with many spatio-temporal variables, it may still be difficult to measure it, let alone measure accurately. A representative example is measuring the size of a crowd. Although its semantics are well defined, in practice it turns out that accurately counting how many people constitute a specific crowd requires highly advanced techniques and skills. Measuring complex variables such as those for mood or emotion is even more challenging.

Sensing a crowd is all about acquiring values for state variables. As mentioned, we distinguish computational from noncomputational methods for data acquisition. For a crowd management framework, both types are important. Yet it seems that the digital sensing of crowd-state variables is still in its infancy, with the exception of video-based solutions. Capturing and analyzing social-media data obtained from, e.g. Twitter or Facebook, can sometimes give an impression of the overall mood of a crowd. More direct measurements of mood can be supported through smartphone applications. Arguably, these are hybrid computational methods of input, as they require explicit actions from users and combine these with automatically sensed input.

The most commonly used, fully automated sensing of a crowd is performed by using video cameras, which can be classified as a computational data acquisition method. A camera is a typical example of an external sensor (also referred to as an ambient sensor): a sensor that is placed externally to the crowd. Another example is that of an ambient microphone. Typically, internal sensors are worn by crowd participants and include accelerators, proximity detectors, (wearable) microphones, etc. Smartphones are a common carrier for these type of sensors, yet it is clear that much work needs to be done before such sensors can be used for practical crowd-state measurements.

Referring to our continual Arnhem city example, sensing or acquiring data about the crowd is performed via video cameras and the Wi-Fi hotspots (automated sensors) and observations by security officers (human sensors). Note that in the case of a human sensor, observing the crowd and interpreting the observations (discussed in the next section) can happen together, in a seamlessly coupled manner.

Actuators are tightly coupled to the actual decision-making: they comprise the instruments that can be used for managing or intervening in a crowd. For the purposes of this paper, the actuators themselves are less interesting, except with regard to their effectiveness and efficiency. For example, if a decision is made to stop people from entering a certain area, different instruments can be used: security officers, barriers, displays, and so on. Each of these will most likely have different effects and will attain those effects at different costs. We expect that effectiveness and (cost) efficiency of an instrument is taken into account when making a decision on how to manage a crowd, but we consider it of minor importance for our further discussion herein.

4.2. Operational: Mining subsystem

Sensors deliver what we refer to as raw data: data representing the uninterpreted observations of various aspects of the current state of a crowd. This raw data generally requires proper interpretation in order to derive meaningful information about what is going on in a crowd. The mining subsystem therefore typically contains many data-mining techniques: classifiers, clustering algorithms, techniques for feature extraction, information-fusion algorithms etc., all aimed at making (more) sense of raw observations.

Human analysis plays a key element in the interpretation of observations. This is clearly the case when dealing with video footage where humans are generally much better at interpreting a situation than any automated analysis. However, computational mining instruments do exist and are important. Consider the following examples:

- *Video feature extraction:* In their review paper on crowd analysis, Zhan et al. [2008] describe different techniques for extracting crowd-related variables from video footage such as density, acceleration, etc. It is not difficult to imagine that video analysis alone may easily contribute many different instruments for interpreting raw crowd data.

- *Proximity graphs:* In another, recent example, Martella et al. [2014] discuss how so-called proximity sensors can be used to represent a crowd as a dynamic graph in which a vertex represents a person, and a link represents the fact that two people are in each other's proximity. This proximity graph can subsequently be used to discover patterns in a crowd, like the formation of lanes, identify if and where clogging occurs, etc. Extracting data from the sensors is part of the measurement system, but the instruments for constructing and subsequently interpreting the resulting proximity graph are part of the mining subsystem.

The effect of the mining subsystem is that observations are brought to a higher level of abstraction by adding a layer of interpretation. The level of abstraction depends on the mining instrument and purpose.

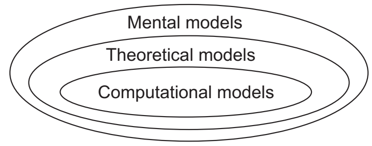

Figure 3: Distinction of model types based on their increasing degree of formalism. An inclusion relation between computational, theoretical, and mental models.

Note that the division between a measured crowd state and the interpreted state is not strict. There are, for example, collaborative sensing systems that can estimate the size and density of a crowd [Cattani et al., 2014].

The output of the mining subsystem will often be presented to human crowd experts through visualizations in order to assist them in decision-making. However, we do not exclude the situation in which interpretations can be directly used for crowd interventions as can be the case for automatically controlling traffic lights or what is being displayed on a public screen.

In our continual example in Arnhem city, mining happens while the video images (i.e., the raw observations) are interpreted by humans at the control room. For instance, the operational manager may interpret the images to define a clogging situation in a narrow street. The Wi-Fi hotspot detections of smartphones add automated support making it possible to identify trajectories of people moving through streets. In this case, combining hotspot information, a city map, and knowledge regarding the location of the living statues and other attractors, and then mining the hotspot data, may reveal particularly popular locations (i.e., where many people stay for a relatively long time), unexpected routes (e.g. related to local densities), or potentially hazardous situations (when multiple trajectories are targeting the same location).

4.3. Operational: Prediction subsystem

The predicting subsystem contains the instruments that generate a possible future state of the crowd. It forms a key component of our framework as predicting possible futures is crucial for making intervention decisions. It uses models as instruments.

We distinguish three types of models in this paper to allow for a meaningful distinction of the level of formalism:

- mental models,
- theoretical models,
- computational models.

Figure 3 shows the inclusion relation of the model types to each other. Models with a high degree of formalism are considered computational models. This includes models that are not actually implemented in a computer system if the level of specification is high enough that the model could be implemented. A theoretical model is a noncomputational model that has been formalized and has scientifically been evaluated, for instance in a social-science theory on crowd behavior. As an example, the initiation-escalation model [Adang, 2011] is a theory that explains under which (social) circumstances the initiation and escalation of violence is more likely to occur.

A mental model is an image of the world that humans have for making sense of and be able to engage with the world. It is an informal model that has not been formalized, scientifically evaluated, (e.g., not communicated, not specified, not written down, not generalized, not systematically analyzed, not peer-reviewed). Compared to a computational model, mental models are mostly tacit, i.e., not precise, but ambiguous and not necessarily conscious [Forrester, 1971]. To illustrate, an expert is often not able to externalize her knowledge, but still has an internal representation of the world that allows her to perform her expert task.

The output of the predicting subsystem depends on the type of model that is used. Both mental and theoretical models produce a future *interpreted* state of the crowd. In other words, the state of a crowd is already formulated in relatively high-level semantic descriptions.

In the case of computational models, there are essentially two options. First, a model may generate raw crowd data, similar to raw observation data coming from original sensors. Typically, this is done by crowd simulators whose aim is to extrapolate a given trace of raw input data with new data points. A trace, in this context, is a sequence of timestamped events, comparable to a traditional event log. By feeding a simulator with a trace, and subsequently comparing its output (which may again be a trace of predicted events) to the originally captured data from sensors, the predictive ability of the simulation model can be evaluated. The output of such predictors will often need to be processed by the mining subsystem before it can be further handled.

As an alternative, a predictive model may have integrated the generation and interpretation of raw data and instantly produce data at a higher level of abstraction. Its output would then be seen as interpreted data, meaning that it embeds elements that fall under the mining subsystem. An example of this is a model that directly predicts where clogging will take place without first generating the relatively low-level raw-data traces. Normally, the phenomenon of clogging would have to be derived from interpreting such raw data.

In our continual example in Arnhem city, a decision-support system for crowd managers would typically run trace-driven simulations of crowd movements in the downtown area of Arnhem. Those simulations, based on models for predicting how people behave in a crowd, would take recent data from various Wi-Fi hotspots as input and allow an operational manager to perform an analysis given the current situation. In other cases, video footage, perhaps combined with information from the hotspots as well as input from security officers, would allow an operational manager to anticipate what might happen through visual inspection, and take actions accordingly.

4.4. Operational: Decision-making subsystem

Finally, the models, tools, and techniques in the crowd management framework includes support in the form of recommendations for interventions in a crowd. Note that this support is different from providing predictions: the output of this component are recommendations for using(or not using) specific intervention instruments.

The decision-making subsystem focuses on crowd-level goals. An example is safety which could be expressed in terms of maximal acceptable densities, lack of violence, entertainment, etc. The crowd management actions chosen or suggested by the models in this subsystem thus aim to identify the actions required to prepare for, maintain, prevent, or go back to an overall desired crowd state. To illustrate, in order to identify what should be done when clogging could potentially lead to a dangerous situation, a number of steps must take place before the decision-making subsystem is involved: data must be gathered on the clogging, the situation at hand must be recognized as "clogging", and the context in which the clogging is taking place must be determined. Then, for this *recognized situation in context*, the decision-making subsystem must identify specific interventions (e.g. opening additional exits) that could work given the decision-making goals in the context and be able to assess the effects of these interventions. The more global view on what is going on in a crowd—which corresponds to the recognized situation in context in the example above —can be captured in terms of scenarios. A **scenario**, as we define it herein, is a description of the situation which in essence represents the state of knowledge on the situation (i.e., situation awareness). Ideally, it is expressed as a formal computational model, so that it can be used to support decision-making in an automated fashion.

A scenario effectively limits the number of situations that need to be evaluated for selecting an intervention action. For example, in the case of clogging in narrow streets, it may be necessary to facilitate additional exit routes or prevent two-way pedestrian traffic. Whereas, when dealing with high-density crowds in front of a stage, the only alternative may be to close-off entire sections and allow people only to move away from the stage. We can assume the decision-making subsystem to consist of a *generic* rule-based approach towards such a selection, forming the operational output of INCROWD. In this generic rule-based approach, each of a number of possible scenarios is related to one (or more) intervention(s). In this case, we intend context-rich rules, which means that context information (which is part of the scenario description) is essential in triggering the rules (i.e., in determining which interventions are appropriate for a given scenario). Arriving at an appropriate set of rules is also part of our framework, namely as a separate case of model development, to which we return in Section 5. Selecting the appropriate scenarios becomes an essential element of the operational framework, and as noted in Figure 1, this will be carried out by humans as well as automatically.

Finally, we note that a natural way to come to a final recommendation for crowd intervention is by means of *what-if* analyses which here refer to (mental or computational) simulations of how interventions will play out in context. Such *what-if* analyses may be performed automatically, but human participation will often be needed, certainly in complex situations. In the context of operations engineering, there are multiple objectives in decision-making:

- match the situation at hand to one or more recognizable scenarios,
- select one or several intervention instruments,
- simulate and subsequently evaluate what happens when those interventions are exerted,
- possibly modify the selected interventions to fulfill decision-making goals.

Challenging enough, these objectives must also be met in real-time.

5. Model development with INCROWD

Most crowd models are not ready for operational use. To guide the development for operational models further, it is crucial that these crowd models capture and connect the various aspects of crowd management. Consequently, support for **models in development** embeds models that target the diverse stages of crowd management: crowd-interaction (actuating & sensing), mining, prediction and decision-making. The INCROWD framework provides a process structure that embeds model development within the overall decision support aim of crowd management. INCROWD as a framework for model development makes a distinction between (1) models in development and (2) a testing subsystem.

- **Crowd-interaction models**, relate to both **actuation models** and **sensing models**. An **actuation model** describes the anticipated effect of using a specific actuator on the state of a crowd, e.g., mobile barriers to affect flow. A **sensing model** aims at capturing the state of a crowd, and essentially consists of choosing the variables for representing that state, and subsequently the sensors and their values for instantiating those variables, e.g., determining local density.
- **Mining models** are developed for analyzing the measured crowd state and are typically aimed at feature extraction, classification etc.
- **Predictive models** describe the future or anticipated state of a crowd, given an initial state, a situation and possibly data from a mining model.

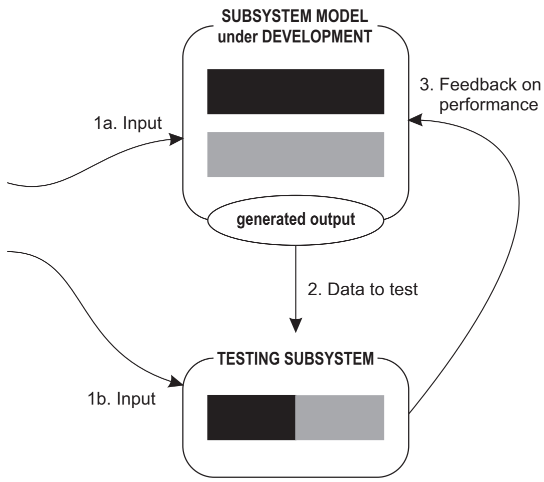

Figure 4: The overview of model development with INCROWD. The mining, prediction, and decision-making subsystems generally develop their models by giving some input and subsequently test a model's output against expected output.

- **Decision-making models** select effective intervention instruments based on a current (high level) description of a (part of a) crowd.

The **testing component**'s purpose is to test how well a model performs by giving feedback and an indication whether the model is considered to be "accepted".

Analogous to operations engineering where the goal is to manage the behavior of a crowd in a continuous iterative process, we speak of **model development**, or model engineering, emphasizing that development of models is also a continuous iterative process: a model in development receives input and generates output that is tested by the testing subsystem. The generated output needs to be compared against the expected output as shown in Figure 4.

Although the process of handling input, generating output, and providing feedback holds for every model in development, the actual model development may differ per subsystem as we explain next. The following subsections will elaborate in more detail on model development related to the mining, predicting and decision-making subsystem, respectively. We concentrate on explaining computational models, but note that our observations equally hold for noncomputational models, such as theory testing using empirical data (theoretical model) or training stewards and crowd managers (mental models). We exclude actuation and sensing models for the reasons that these models are often formed in an ad-hoc and often even implicit fashion, and are not easy to generalize.

5.1. Developing a crowd-mining model

The mining model in development as well as the testing subsystem receive data on the crowd state as input (Figure 4, streams 1a and 1b). This data is considered to be *ground truth*. Data may come from actual measurements or be synthetic. The mining model in development uses the input data and produces output. Both input data and model output feed into the testing subsystem (2). The testing subsystem then produces feedback based on its acceptance procedure (3). Note that the preprocessing of the input data (i.e., an accepted mining model) for the testing subsystem can also reside within the testing subsystem. Given the feedback, the mining model is adapted and the next iteration takes place until the model in development becomes accepted.

Take, for example, the development of a model $\hat{M}$ for the identification of crowd patterns based on smartphone detection through the Wi-Fi hotspots in our continual Arnhem example. In this case, model

$\hat{M}$ needs to extract a pedestrian lane within a crowd from the smartphone movement detections. At the same time, there may be video footage available for the area in question that allows an operational manager to detect whether lanes have formed. Using human (dis)approval, model $\hat{M}$ can be gradually refined until it is accepted as a lane extraction technique. Note that input 1b is not strictly necessary, in which case a modeler will be dealing with unsupervised learning.

5.2. Developing a crowd-predictive model

The process involved in developing a crowd-predictive model is very similar to that of a crowd-mining model. Data is received on the state of a crowd (1a,1b), and is again considered to be *ground truth*. The model produces output (2) that needs to be checked against the original input, leading to feedback (3) for further fine-tuning. The input-output-feedback cycle typically iterates until the performance feedback is considered *validated* and the model is considered an "accepted" model in the prediction subsystem. Note that the generated output of the prediction subsystem and the *ground truth* need to be "comparable". This means that either or both types of data may need to be first interpreted by an accepted mining subsystem model, which takes place inside the testing subsystem, see e.g. [Antonini et al., 2004a].

In our continual example of the city of Arnhem, sequences of movement measurements over time, i.e. traces, from smartphone movement detections could be used as input to models that simulate crowd movement, i.e., can predict clogging. Assuming a trace spanning a time interval $[0,T]$. By using a subtrace $[t_1,t_2] \subset [0,T]$ as input for simulations, a modeler can observe the state $\sigma^*(\tau)$ of (a part of) the crowd at any time $\tau \in (t_2,T]$ as produced by the simulator and compare it to the actual observed state $\sigma(\tau)$. Such comparisons will allow for refining the simulation model.

5.3. Developing a decision-making model

A model in development as part of the decision-making subsystem aims at developing a generic rule-based decision-making model that is able to suggest situation-based action for intervention. Typically, such a decision-making model relates each of the (possible) scenarios it receives, or extrapolates itself, to a matching intervention.

The process for developing a model in this case is somewhat different than in the previous two cases. First, the input (1a in Figure 4) is a "scenario". As an example, consider the scenario of a crowd in front of a stage at a festival. Another scenario is that of a crowd waiting to enter a building. Both scenarios describe a situation in which many people are standing still. However, for each scenario different density levels should alert a crowd manager but also might involve suggesting different interventions to lower the density.

Based on the crowd scenario, the decision-making model provides an intervention as output, which then needs to be evaluated. The testing subsystem receives a scenario-based goal (1b in Figure 4) and the generated intervention to evaluate whether applying the intervention for the given scenario likely results in the predefined goal or not. The goal is based on the prescribed standards related to that particular scenario. Usually these goals revolve around safety, public order, or fun levels. For example, keeping crowd density in a given area below a certain value is a typical safety goal. In order for the testing subsystem to come to an evaluation, the impact of the suggested intervention first needs to be 'produced'. This can be accomplished either by implementing the intervention using an accepted model from the prediction subsystem (e.g., computationally simulating what happens if the intervention is executed) or by sensing (and mining) the results of an actual intervention implementation in a crowd. Given the feedback of the testing subsystem, the decision-making model is adapted and enters a next iteration until the scenario-intervention link is considered suitable by the testing subsystem [Schubert and Suzic, 2007].

For a decision-making model in development to become accepted, multiple embedded iterations of the scenario-intervention rule-learning cycle need to take place. This requires that appropriate rules relating

Table 2: Key differences in model development between the different subsystems.

	Mining models	**Predictive models**	**Decision-making models**
Goal of model	Classify, or cluster raw crowd data; extract specific features from raw data	Generate a future (interpreted) state	Select a crowd intervention action for a given interpreted state (a *scenario*)
Input	Data	Data	Scenario
Output	Data interpretation	Crowd state	Intervention action
Feedback	Match output interpretation to expected interpretation	Match generated state to expected next state	Indicator on impact of suggested intervention in the given scenario, given decision making goals
Learning Process	Iterate until accepted	Iterate until accepted	Iterate until all links between scenario and interventions are learned *and* accepted
Testing	Comparison: has the model mined what was to be expected?	Validation: how good is the predicted output?	Sensibility: is the proposed intervention reasonable for the given scenario?

scenarios and interventions should be learned for all concerned scenarios. Therefore, only when the appropriateness of the rules for all scenarios has been established, will the model be considered validated and thus become an accepted model.

In our continual example, we assume that a potentially dangerous situation is encountered, e.g., clogging at a narrow street in the downtown area. The context, consisting of a narrow street and two streams of pedestrians moving in each others direction, as well as several pedestrian movements from side streets, may lead to the conclusion that barriers need to be placed to direct pedestrians in a single direction only, corresponding to a possible intervention for handling the scenario. To predict whether the intervention will likely produce the expected results for that scenario, the scenario-intervention pair can be fed to a real-time simulator (an accepted predictive model) and the simulated results can be analyzed (by humans or an accepted mining model) against the decision-making goals. If deemed effective, the barriers could be implemented in a fully automated manner as well as information boards providing information, traffic lights, or even automated road blocks. In a practical setting, an operational manager would provide instructions to security officers to move to one end of the street to prevent more people from entering through that end.

Table 2 summarizes the various approaches we have discussed.

6. Research on crowd management: a status report

Crowd management commonly strives for safe and enjoyable crowd events. We regard crowd management as a chain of integrated stages in which crowd managers (possibly aided by automated systems) monitor, interpret, anticipate, and act, as described in Sections 2 and 3). The ways in which crowd research addresses this objective of crowd management are rather diverse. We will use the INCROWD framework as a lens to provide an extensive overview of the various foci and practices. Particularly, as we shall motivate below, we focus on models in development: what subsystems they focus on, whether they make use of input, and their testing practices.

This review covers 237 papers, selected as a representative sample of crowd models. The base set consists of 59 papers and was mainly derived from several review papers [Challenger et al., 2009b; Bellomo and Dogbe, 2011; Davies et al., 1995; Wijermans, 2011; Zhan et al., 2008]. Each of these review papers had its own aim and purpose. However all addressed a relevant scope of crowd models from the perspective of operational support ([Challenger et al., 2009b]), sensors (see, for example, [Baratchi et al., 2013]), or models in the social sciences ([Wijermans, 2011]). To ensure that we capture a representative set, we extracted 142 papers from the references of the base-set papers and 36 from the Safety Science journal based on a key-word search (crowd).

The papers included in this review aim to contribute to crowd management and together represent the modeling diversity in crowd research. The extended set of papers were extracted from the papers found in the review paper references (310) and in the Safety Science journal (144). We excluded a paper when it was considered off-topic, had an equipment testing focus or was a reflection on crowd management. More specifically, of the papers that discussed models, two types of models were typically excluded. Firstly, we excluded models that do not aim to contribute to crowd management but aim to demonstrate a particular method (e.g. [Epstein, 2002]). Secondly, we excluded models that were already represented by one or more core models. For instance, there exist many adaptations or specifications of the social-force model [Helbing and Molnar, 1995]. We thus do not claim completeness in this review, but rather the representativeness of the wide range of crowd research and reflect on the foci and practices in model development.

6.1. Review protocol

Our review uses the INCROWD framework as a lens, which means that each paper in the review has been classified: the framework view, the type of model, and subsystems involved were identified. The framework view (operational or development) was identified based on whether the model is in use (operational) or in development. The type of the model (actuating, sensing, mining, prediction, or decision-making) relates to the subsystem in focus. Any other subsystem involved in the model was also indicated. For the set of models in development, we also indicated whether they had some input and how they were tested, if at all. If a model reported to make use of an input, we specified whether this input was used for model design or as input data. Model design input specifies which type of input the model design choices were based on, e.g., use of a mental model, theoretical model, computational model, or data-driven design choices. The data input specifies the purpose for which data was used besides model design, e.g., training, calibration, initial settings, or scenarios. To consider whether a model was tested, we identified the model aim, the evaluation procedure and whether the authors considered their model tested. For details on the mapping procedure and also the extensive final dataset of mapped papers, please see the supplementary data. The classification work was carried out as follows.

For the base set, consisting of 59 papers:

Phase 1, parallel classification The papers were divided into two subsets (A and B). For each subset of papers, two of the authors (A1, A2, B1, B2) were assigned to review and classify the papers independently in parallel. This procedure allowed us to test the applicability of our framework, while also reducing the influence of our unavoidable disciplinary biases in classifying models from other disciplines. We note that the five authors all have different disciplinary backgrounds: cognitive science, physics, computer science, and industrial design and engineering.

Phase 2, preparing the merge Each subset (A and B) were then prepared by one reviewer from the respective other subset (A by B1 and B by A1). The preparation consisted of finalizing a classification (possible when a paper was put in the same category by both reviewers), and highlighting differences when a paper was not unanimously classified.

Phase 3, the merge In a meeting, with the original reviewers of each subset, the incongruent categorizations were discussed and decided together on the papers final classification. In the process of discussion, the framework description was reflected upon and improved. Finally, all classifications were merged into the final dataset.

For the additional 142 + 36 papers, we proceeded as follows:

Phase 1, individual classification All papers were distributed among the team of five author-reviewers according to expertise, and subsequently classified individually. In doubt, a second opinion was sought from within the team.

Phase 2, second opinion Papers marked for a second-opinion where evaluated, discussed and decided upon together in a meeting.

6.2. Results

Mapping the 237 papers, at first glance shows a major division in model types: 89% of the models are computational models, the remaining 11% are theoretical models. No mental models were covered. This skewed distribution of models may be attributed to the different traditions of the natural sciences versus the social sciences: The use or reference to existing models and a formal level of description are more present in natural sciences that produce computational models, compared to the social sciences that, if any, produce theoretical models. The result of no paper discussing a mental model was to be expected. Mental models are generally not described and form part of the tacit expertise of crowd management practitioners. Regarding the operational versus the developmental view of the INCROWD framework, most models (94%) are in development. The relatively low presence of operational models in our literature review is more difficult to explain. It may indicate that these models are typically developed outside of academia, hence not reported as publications in academic journals, or that these models are simply not so abundant. We therefore continue by concentrating on the models in development (223), see the supplementary data for the dataset and analysis of mapped papers.

Model focus

As shown Figure 5, most models in development belong to the prediction subsystem, followed by mining subsystem models, while only a few papers focus on the sensing and decision-making subsystems and, in fact, only one single paper addresses the actuating subsystem. All of the models in development, except for six, indicate the use of design or data input for their models. This concerns any input for model design or the use of raw or interpreted data that feeds into the model due to, for example, training, calibration, initial settings, and scenarios.

The INCROWD framework emphasizes the importance of an integrative view on crowd management: each subsystem is needed and is dependent on every other subsystem. Without making any judgments regarding the applicability of current developments for crowd management, the presence of these interdependencies embodies a promise for the (future) ability to support crowd management. As shown in Table 3 most models depend on an (accepted) model from another subsystem. For example, Andersson et al. [2009] train their mining model to detect abnormal behavior using sensing data from a mix of sensors, such as surveillance cameras, thermal infrared cameras, radar, and acoustic sensors.

The development of sensing and decision-making models show a strong dependence on the use of accepted models from the mining and the predicting subsystem. Furthermore, as to be expected, the development of sensing and mining models depend less on the predictive and decision-making models than the other way around. There are, of course, exceptions of sensing and mining models that make use of predictive models (such as [Antonini et al., 2004c]) or decision-making models (such as [Andersson et al., 2009; Drews et al., 2010; Roggen et al., 2011]), respectively. The predictive models vary in their incorporation of other subsystems. Most of them do not rely on any other subsystem. However, of those that do relate to other subsystems, we see a variation of combinations. For instance, combinations with sensing models [Drury and Reicher, 1999, 2000; Moussaïd et al., 2011]; with decision-making models [Helbing, 1992; Helbing et al., 2000]; with mining models [Murakami et al., 2002]; with both sensing and mining models [Lee and Hughes, 2007; Moore et al., 2008]; and even combinations that relate the predictive model to all other three subsystems [Johansson et al., 2008; Still, 2000].

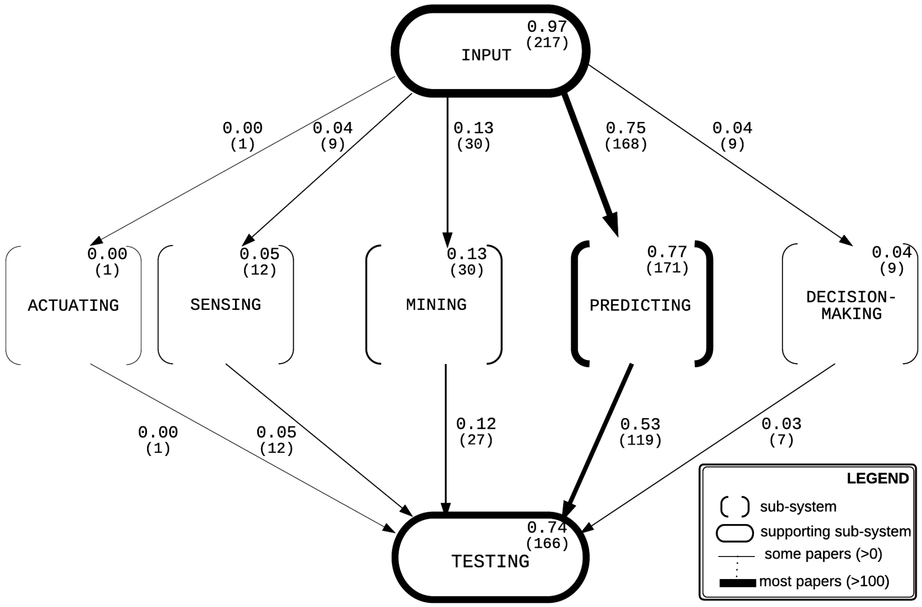

Figure 5: Overview of the 223 papers describing models in development. Shows the research attention, the input and evaluation of the models per subsystem. Provided in fractions, with absolute numbers in parentheses.

Table 3: The fraction of models in development that depend on other subsystems. Absolute numbers are in parentheses.

	Subsystem on which model depends				
Model in development↓	A	S	M	P	DM
Actuating (A)	1.00 (1)	0.00 (0)	0.00 (0)	1.00 (1)	1.00 (1)
Sensing (S)	0.00 (0)	1.00 (12)	0.58 (7)	0.33 (4)	0.00 (0)
Mining (M)	0.00 (0)	0.33 (10)	1.00 (30)	0.20 (6)	0.13 (4)
Predictive (P)	0.01 (2)	0.17 (29)	0.20 (34)	0.99 (170)	0.15 (25)
Decision-making (DM)	0.00 (0)	0.11 (1)	0.33 (3)	0.89 (8)	1.00 (9)

Context

Crowd management is related to a wide range of crowd contexts. Table 4 gives an impression of the range and attention for different contexts by the models in development. Note that for each paper number (refID), the corresponding citation and reference can be obtained using Table A.7 and the references.

The context of a model refers to the situation or phenomenon the model is supposed to operate within. In our review we discern:

- **Extreme context**: the models apply to extreme crowd situations, such as emergencies (panic, danger, evacuation), escalation (violence, aggression, conflict), military context (urban combat, peacekeeping) and large-scale crowd situations where density or size are the defining characteristic for the extreme setting.

- **Generic context**: the models apply to non-extreme, general crowd contexts including normal pedestrian situations and gatherings.

- **Context-independent context**: the models operate in any context, not restricted to a particular crowd context or crowds.

Table 4 shows our findings regarding the context of models in development. Most attention is dedicated to the generic, non-extreme crowd context, of which the majority focuses exclusively on pedestrian crowds. For example, Moore et al. [2008] aim to generate walking behavior of pedestrian crowds in city centers while being under the influence of alcohol. The remaining generic models do not specifically focus on pedestrians.

The second largest group of models target extreme contexts. However, what is considered extreme is quite diverse: emergencies, escalation, military context, or the large scale of a crowd event. Lastly, there are a few context-independent models applied to a crowd context. For example, Martella et al. [2014] aim to sense social dynamics of a group of people in the form of a spatio-temporal social graph from noisy proximity data applicable in any crowd context (emergencies, riots etc.). The same holds for Roggen et al. [2011] who aim for recognizing crowd behavior from on-body sensors (i.e., from mobile phones). The majority of the predictive models cluster around the generic-pedestrian and extreme-emergency contexts, whereas mining models pay attention to the generic-pedestrian and extreme-large scale contexts.

Table 4: Models in development categorized based on context. Context refers to the situation in which the model is supposed to actuate (A), sense (S), mine (M), predict (P) or decide (DM). Provided in fractions, with absolute numbers in parentheses.

Context	Sum	A	S	M	P	DM	refID
Extreme: Emergency	0.36 (81)	0.00 (1)	0.01 (3)	0.01 (3)	0.31 (69)	0.02 (5)	1, 3, 8, 10, 16, 17, 18, 20, 26, 28, 32, 33, 34, 35, 41, 42, 48, 50, 55, 56, 57, 61, 65, 66, 70, 71, 73, 75, 79, 80, 93, 94, 99, 102, 114, 115, 116, 118, 119, 120, 121, 122, 123, 124, 125, 139, 140, 150, 151, 152, 153, 155, 156, 157, 159, 160, 162, 165, 166, 179, 180, 181, 186, 187, 190, 191, 192, 198, 199, 200, 213, 215, 216, 218, 219, 221, 222, 228, 231, 235, 238
Extreme: Escalation	0.05 (11)	0.00 (0)	0.00 (0)	0.01 (2)	0.03 (7)	0.01 (2)	2, 37, 44, 45, 53, 89, 98, 169, 176, 193, 194
Extreme: Large scale	0.07 (16)	0.00 (0)	0.00 (1)	0.03 (7)	0.03 (7)	0.00 (1)	5, 6, 7, 9, 27, 87, 90, 91, 108, 110, 134, 147, 161, 168, 171, 223
Extreme: military	0.01 (3)	0.00 (0)	0.00 (0)	0.00 (0)	0.01 (3)	0.00 (0)	149, 177, 184
Generic: pedestrian	0.41 (92)	0.00 (0)	0.03 (7)	0.07 (16)	0.31 (69)	0.00 (0)	4, 13, 14, 15, 19, 21, 24, 25, 29, 30, 36, 38, 39, 40, 51, 58, 59, 60, 62, 63, 64, 67, 68, 69, 72, 76, 77, 81, 82, 83, 84, 85, 86, 95, 100, 101, 103, 106, 107, 109, 111, 112, 113, 126, 127, 128, 130, 131, 133, 135, 136, 137, 138, 141, 142, 143, 145, 146, 148, 154, 158, 163, 164, 167, 170, 173, 174, 175, 178, 182, 183, 188, 189, 202, 203, 205, 206, 207, 209, 211, 212, 220, 224, 225, 226, 227, 230, 232, 233, 234, 236, 237
Generic: Other	0.04 (10)	0.00 (0)	0.00 (0)	0.00 (0)	0.04 (10)	0.00 (0)	23, 46, 47, 52, 54, 92, 196, 201, 208, 214
Context-independent (neutral)	0.04 (8)	0.00 (0)	0.00 (1)	0.01 (2)	0.02 (4)	0.00 (1)	12, 49, 132, 172, 185, 195, 204, 210
Not fitting	0.01 (2)	0.00 (0)	0.00 (0)	0.00 (0)	0.01 (2)	0.00 (0)	22, 144
Total	1.00 (223)	0.00 (1)	0.04 (12)	0.13 (30)	0.76 (171)	0.03 (9)	

Behavior target

We now concentrate on the behavior that the models are targeting. In this case, we refer to the behavior the authors claim to (re)produce, measure, influence etc. with their model. In our review we distinguish between the following behavior targets:

- **Motion**: when authors focus on movement, walking, grouping, collision avoidance, crowd dynamics, queuing, herding, lane formation, flow oscillations, competition, density, clogging, etc. They typically aim at modeling movement from a start position to a final goal position, taking into account direction, speed, and obstacle avoidance [Moussaïd et al., 2011].

- **Collective violence**: when authors focus on fights, riots, robbery, incidents, public order, as well as anomalous behavior related to violence.

- **Conformity**: when authors focus on consensus, exemplified by aligned behaviors, same opinions, and/or emotions, and so on (see, e.g. [Feinberg and Johnson, 1990; Johnson and Feinberg, 1977; Tarnow, 1996]).

- **Psychological change**: when authors focus on internal, mental processes. For example, there are various papers that describe the process in which behaviors change based on individuals identifying themselves as part of a social group [Drury and Reicher, 2000; Drury et al., 2009].

- **Diversity of crowd behaviors**: in case the authors target a multiplicity of behaviors. For example, Nguyen et al. [2005] aim to simulate a large repertoire of behaviors in a crowd relevant to modern military operations, such as wandering, standing, climbing, pushing, and shooting.

- **No behavior target**: when authors do not focus on any specific behavior type, but more on e.g. measuring proximity or tracking people in a crowd.

We summarize our findings in Table 5. Models with motion as the behavior target form by far the largest group. This group is often also referred to as crowd dynamics models. The group largely intersects with the groups with a generic-pedestrian context and an extreme-emergency context. In addition, the motion-model group is mainly populated by predictive and mining models. Models that target a diversity of crowd behaviors and collective violence reflect the next biggest behavior target focus. Like the motion models, they are both dominated by predictive models. The models target at no specific behavior and the motion models are relatively diverse in terms of focal subsystem, but mostly they involve sensing and mining models.

Model input

Almost without exception, the investigated models in development make use of inputs for their design or use input data to train, calibrate, or initialize their model (recall Figure 5). In this subsection we highlight what is communicated about the design of models as well as the use of (interpreted) data in model development.

Model design is one of the most important—and at the same time the least communicated—stages of modeling. Therefore, we provide an impression of the sources of crowd models, at least for the cases in which these were mentioned, and summarized in Figure 6. The design of computational models is often based on other computational models, and to a lesser extent on theoretical models, or on data. Often a combination of sources was used to develop computational models. For example, for the *Legion* model of crowd dynamics during emergencies, Still [2000] uses data for calibration as well as theoretical models to derive psychology-based rules to design his agents. In the *CROSS* model, both theoretical and computational models are used to model crowd behavior [Wijermans et al., 2013]. In *CROSS*, the theoretical model adopts psychology-based variables and rules for model design, similar to *Legion*. The computational model used in CROSS refers to the model design choice to adopt the structure of cognitive architectures. When we look at the design of theoretical models, they are based on other theoretical models, on data, on computational models, or on a combination of them.

Table 5: Models in development categorized based on the behavior they target. The behavior target refers to the behavior the model targets to affect (actuate - A, or sense - S), to interpret (mine - M), to (re)produce (predict (P), to decide on (DM).

Behavior target	Sum	A	S	M	P	DM	refID
Collective violence	0.05 (11)	0.00 (0)	0.00 (0)	0.01 (2)	0.03 (7)	0.01 (2)	2, 37, 44, 45, 53, 89, 98, 169, 176, 193, 194
Conformity	0.03 (6)	0.00 (0)	0.00 (0)	0.00 (0)	0.03(6)	0.00 (0)	23, 54, 92, 186, 195, 196
Diversity of crowd behaviors	0.07 (16)	0.00 (0)	0.00 (0)	0.00 (1)	0.06 (14)	0.00 (1)	3, 9, 21, 26, 49, 52, 57, 149, 177, 184, 187, 200, 204, 214, 225, 228
Motion	0.75 (167)	0.00 (0)	0.03 (6)	0.10 (22)	0.61 (135)	0.02 (4)	1, 4, 5, 6, 7, 8, 10, 13, 14, 15, 16, 17, 18, 19, 20, 24, 25, 28, 29, 30, 32, 33, 34, 35, 36, 38, 39, 40, 41, 50, 51, 55, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 75, 76, 77, 79, 80, 81, 82, 83, 84, 85, 86, 91, 93, 94, 95, 99, 100, 102, 103, 106, 107, 109, 110, 111, 112, 113, 114, 115, 118, 119, 120, 121, 122, 123, 124, 125, 126, 128, 130, 131, 133, 134, 136, 137, 138, 139, 140, 141, 142, 143, 145, 146, 147, 148, 150, 151, 152, 153, 154, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 167, 170, 172, 173, 174, 175, 178, 179, 180, 181, 182, 183, 188, 189, 190, 191, 192, 198, 199, 201, 202, 203, 205, 206, 207, 208, 209, 210, 211, 212, 213, 215, 216, 218, 219, 220, 221, 222, 224, 226, 227, 230, 231, 232, 233, 234, 235, 236, 237
Psychological change	0.02 (5)	0.00 (0)	0.00 (1)	0.00 (0)	0.01 (2)	0.01 (2)	46, 47, 48, 166, 185
No behavior target	0.06 (13)	0.00 (0)	0.02 (4)	0.01 (3)	0.03 (6)	0.00 (0)	22, 56, 87, 90, 101, 108, 116, 127, 132, 135, 144, 168, 171
Not fitting	0.02 (5)	0.00 (1)	0.00 (1)	0.01 (2)	0.00 (1)	0.00 (0)	12, 27, 42, 223, 238
Total	1.00 (223)	0.00 (1)	0.05 (12)	0.13 (30)	0.77 (171)	0.04 (9)	

Model testing

To assess the quality of a model and its application domain, model testing plays a crucial role in model development. Most models were considered 'tested' by their authors. Among the tested models, a striking diversity in evaluation procedures appeared (see Table 6). If the goal is to develop accepted models for crowd management, model validation must be part of the evaluation procedure. However, model validation means different things for each model type in our framework, as it involves determining whether the model can accurately:

- capture relevant data for the target behavior (sensing model),
- detect or recognize the target behavior (mining model),
- represent or anticipate the target behavior (predictive model) [Law, 2015; Balci, 1995],
- suggest the adequate intervention for handling the target behavior (decision-making model), or
- handle or deal with the target behavior (actuating model).

Departing from the models that were considered tested by their authors, we consider further classifying models based on whether or not they include a reference to an empirical crowd phenomenon. The evaluation of the models that exclude an empirical phenomena include tests of *computational performance*, e.g. tests of computational speed [Narain et al., 2009], and *theory testing*, i.e., model explorations

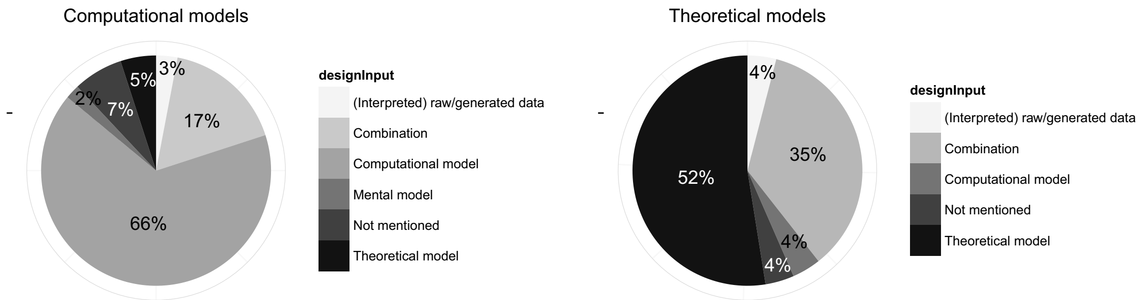

Figure 6: Design input used by models in development, specified for computational (left) and theoretical (right) models.

as an evaluation of their model. The theory testing group thus use their models as an accepted model, i.e., a model that has been tested positively in relation to the empirical phenomenon. For instance, Moore et al. [2008] test the influence of alcohol on gait, whereas Feinberg and Johnson [1990] test the influence of the presence of social bonds on the emergence and speed of consensus.

The majority of the tested models incorporate a reference to an empirical crowd phenomenon in their evaluation. Mostly used is output validation, i.e., the evaluation of the model based on the link between the behavioral target and the empirical phenomenon. The papers performing output validation are grouped into *nonsystematic* and *systematic* evaluation procedures. Of the models referring to an empirical crowd phenomenon, about half have a *nonsystematic* evaluation procedure. This concerns papers that make loose referrals to reality, for instance, tests based on visual inspection by the model designer, use of stylized or general observed empirical patterns, references to common knowledge, anecdotal evidence, etc. Of these papers in the nonsystematic group, most are both predictive and computational models. Nonsystematic evaluation usually involves no external source of evaluation other than the modeler in person. The focus lies on finding evidence to support the model, not on explicitly testing them in a way that could lead to a negative evaluation.

The other half of the models evaluated with a reference to real-world phenomena are categorized as systematically evaluated. A *systematic* testing procedure includes comparisons following a method, such as measuring a goodness-of-fit using statistical analysis or a comparison with other accepted models. In contrast to the nonsystematic group, which is dominant among predictive models, the systematic group includes models from all subsystems. Interestingly, the predictive and mining models in our review dominate in the group using a systematic evaluation procedure. Zooming in a bit further, systematic evaluation making use of qualitative (descriptive) data is done to a lesser extent than systematic evaluation using quantitative (numerical) data.

These results indicate that there is not one "common rigor" when it comes to model evaluation. This diversity concerns particularly the predictive models, whereas all the mining models seem to have a higher demand for evaluation as well as a common way to perform and communicate their model evaluation. In the conclusions, we will further reflect on these results and propose a research agenda for crowd management.

7. Conclusions

In this paper, we proposed the decision-support framework INCROWD guiding towards more integrated support in operational *crowd management*. Managing crowds is important, if only for purposes of general safety. As explained, current practice is such that much effort is spent on *preparing* events so that no or minimal intervention is needed during an event. However, it is generally accepted that preparation alone is not sufficient, meaning that monitoring crowds during an event and anticipating interventions

Table 6: Models in development categorized based on the evaluation procedure of those models for which the authors consider the models tested. Provided in fractions, with absolute numbers in parentheses.

Eval.	Sum	A	S	M	P	DM	refID
I	**0.32 (53)**	0.01 (1)	0.01 (1)	0.02 (4)	0.28 (47)	0.00 (0)	7, 10, 14, 16, 19, 24, 28, 29, 42, 52, 56, 58, 59, 63, 68, 69, 70, 71, 73, 89, 91, 92, 100, 106, 107, 109, 113, 133, 146, 161, 162, 163, 173, 175, 180, 181, 188, 189, 191, 193, 201, 202, 203, 208, 209, 210, 213, 215, 223, 225, 226, 236, 237
II	0.13 (21)	0.00 (0)	0.00 (0)	0.02 (4)	0.09 (15)	0.01 (2)	13, 36, 39, 45, 46, 60, 72, 79, 81, 90, 99, 114, 122, 131, 166, 183, 194, 220, 227, 233, 238
III	**0.34 (57)**	0.00 (0)	0.05 (8)	**0.10 (17)**	**0.17 (29)**	0.02 (3)	3, 9, 15, 25, 27, 37, 38, 44, 48, 50, 51, 61, 64, 75, 87, 95, 101, 102, 108, 110, 112, 115, 118, 119, 120, 126, 127, 128, 132, 134, 135, 137, 138, 139, 140, 145, 156, 157, 167, 168, 170, 171, 172, 174, 176, 179, 182, 186, 192, 195, 199, 206, 222, 224, 231, 232, 234
IV	0.10 (16)	0.00 (0)	0.00 (0)	0.01 (1)	0.08 (13)	0.01 (2)	12, 49, 57, 65, 66, 116, 143, 144, 147, 151, 153, 160, 185, 187, 204, 218
V	0.05 (9)	0.00 (0)	0.00 (0)	0.01 (1)	0.05 (8)	0.00 (0)	33, 53, 54, 80, 93, 94, 136, 164, 198
VI	0.06 (10)	0.00 (0)	0.02 (3)	0.00 (0)	0.04 (7)	0.00 (0)	4, 8, 17, 26, 41, 76, 125, 154, 178, 216
Total	1.00 (166)	0.01 (1)	0.08 (12)	0.16 (27)	0.71 (119)	0.04 (7)	

I: Link to real phenomenon: nonsystematic
II: Link to real phenomenon: systematic, descriptive
III: Link to real phenomenon: systematic, numerical
IV: No link to real phenomenon: computational performance
V: No link to real phenomenon: theory testing
VI: Not fitting

remains essential. To do so, it is important to accurately measure what is going on, properly interpret what is being measured, predict what may happen and select suitable interventions by making optimal use of expertise, knowledge, data and tools, i.e. integrating different crowd models. INCROWD reflects and integrates these different aspects needed to support crowd management: crowd interaction (actuating and sensing), mining, predicting, and decision-making. In other words, (semi-)automated support for decision-making during crowd events, if only for the sake of safety, is important.

Our framework functions as an architecture for supporting decision-making in crowd management as well as for the development of accompanying models. In particular, for real-time support during a crowd event, we regard crowd management as a continuous process in which operations are continuously refined by making use of new information, feedback on earlier interventions etc. This is the reason why we speak of **operations engineering**: INCROWD assists in engineering and developing the operations of managing a crowd. Developing such models is an integral part in our framework, an integration we consider to be important, reflecting the same continuous development until a model is acceptable for use, where it can be further refined.

The INCROWD framework thus provides guidance towards integrated support by making crowd management explicit as subsystems in a decision-support system; how these connect and depend on each other towards an actual decision; and how the sequence of iterations through the subsystems reflect a continuous process for decision support. In particular, we firmly believe in the integration of the strength of both human expertise (assessing complex situations) and computational power (obtaining, processing and filtering huge amounts of information in little time).

The direct use of the INCROWD framework for crowd practitioners and crowd researchers is to enable reflection and actually seek and connect to relevant crowd models. The framework provides concepts to identify the main focus of their work within the chain of crowd management tasks; helps identify which relevant connections can be made to other subsystems; and provides a common language to address these connections irrespective of the type of model (be it a mental, a theoretical or a computational model). The literature review thus also serves as a set of examples to facilitate the search for relevant models beyond task or disciplinary scope.

In particular, for crowd research we used our integrative INCROWD framework as a lens to reflect on the current state of crowd research. In this reflection, we firstly consider the way research is actually (close to) providing operational support; and secondly, what future crowd research should focus on.

7.1. Actual operational support

In our review we find only few models that can be considered operational, i.e., usable for actual crowd management. Our research suggests several reasons for this lack of operational support. Model development is still mainly work in progress and there is a mismatch between, on the one hand, the need for data, testing, and making models fit for operation, and on the other hand, the relatively little attention these issues receive in research. Most scholarly attention is dedicated to model development.

The diversity of existing models reflects the diverse reality of crowd behavior and events. It comes as no surprise that there is no definitive model that captures all necessary knowledge about crowd behavior; it might even be impossible to strive for one. Somewhat troublesome is the fact that almost a quarter of the models under development seem not to have been tested or systematically validated, which obviously hinders their acceptance in actual crowd management support systems.

Although predictive models receive relatively much attention, the opposite can be said for research on how to sense a crowd. Apart from a study on ways to monitor wildlife [Baratchi et al., 2013], which also refers to the applicability in the case of monitoring human mobility, there is, to the best of our knowledge, no systematic study on how to gather information on crowd movements. In addition, although there are by now datasets on mobility (see, for example, the CRAWDAD collection [Kotz and Henderson, 2005]), few datasets are available on massive crowd movements. Effectively, the lack of a systematic study on how to best measure crowd movements, combined with few available datasets, puts model developers in a challenging position: it becomes difficult to develop models that have been scientifically validated, let alone develop models that can justifiably be put to operational use. Similar conclusions can be drawn for the relatively few papers on the decision-making subsystem. In light of our discussion, we see two reasons for this. First, crowd management support is still in a phase of developing appropriate models, and before research can even focus on the decision-making phase, it is essential that those predictions can be trusted. Second, (semi-)automated decision-making support requires more than just computational models: there is also a need to include context information and involvement from human operators. In other words, (semi-)automated decision-making is an inherently difficult task. Nevertheless, we would have expected to see more scientific work in this area as there is so much need for proper support [Challenger et al., 2009b].

To summarize, although much research on crowds is currently undertaken, actual operational support is provided only scarcely. We expect that an operational decision-support system for crowd management would incorporate a multitude of models, each operating at different scales (a person, a group, the crowd as a whole), and validated through proper data sets and testing. Besides the need for sensing, mining, prediction and decision-making research, a rather necessary improvement lies in validation. Moreover, much work is still needed to put developed models to work: how can predictions be used effectively? Do scientists actually study the crowd behaviors that would support crowd managers? Is there a dialogue between researchers and crowd managers to align needs and focus?

7.2. *Points of attention for crowd research*

Taking this review as our starting point, it is now possible to identify several areas of crowd research that deserve more attention to move closer to operational crowd management support. We distinguish between improvements that involve aspects of model development, i.e., validation, multi-scale techniques and interaction between disciplines (within and outside of science), as well as particular needs to sense and mine data for decision-making tools to bring it all together and move towards more actual support.

Model development – general points for improvement. It is clear from our review that much scholarly attention is already dedicated to model development. We explained that model **validation** is an important issue that needs improvement. This is crucial if research wants to take the next step toward practical crowd management support. Apart from validation issues, crowds remain difficult phenomena to model, and it can be expected that models are needed at different crowd scales: a person, a group, a whole crowd. The need for **multiple scales** brings us to a general observation that has also been made in other fields, namely that there is a need for developing multi-scaling techniques. In essence, such techniques allow for linking micro-level models to models that comprise the collective behavior of a crowd (see,e.g. [Bellomo et al., 2013; Tosin, 2014]). Although research is already being conducted in this area, we anticipate that much more is needed for arriving at crowd management support systems.

Lastly, we want to stress the importance of more **interaction within crowd research** (i.e., connecting to other disciplines and fields) and **between crowd research and practice**. Conducting interdisciplinary integration can help make use of and focus on necessary knowledge and tools accumulated in relevant disciplines. It can also contribute to working with a relevant focus that aligns crowd research with the needs of crowd managers. In particular, within (crowd) research it seems quite common to stay within ones own discipline or niche. Particularly, the connection between computer science and the social sciences is not well developed. Hence, our paper also serves to point out relevant existing models, valuable for crowd researcher in any discipline. Ignorance of former research, even if stemming from other domains, holds the danger of using outdated ideas i.e., perpetuating myths and thus potentially cause (or not prevent) harmful operational consequences [Wijermans et al., 2013].

The need for more data – more focus on crowd sensing and mining. As noted, there is relatively little research on how to automatically sense what is happening in a crowd. Data sets are gradually becoming available, but little systematic thought has been given to the data that scientists would need, and subsequently how such data could be automatically obtained through various sensing mechanisms, exceptions are, for instance, [Bernardini et al., 2016; Siddiqui and Gwynne, 2012]. Related, we also observe that mining crowd data is still in its infancy; not surprisingly, since crowd research is still dealing with the lack of sufficient data. It appears to us that there is a lot to gain here, if only for the reason that mining crowd data sets will help researchers validate predictive models. The use of sensing data may lead to an impulse towards developing and validating adequate models and tools for crowd management [Gwynne et al., 1999; Bryan, 1999].

The need to move to actual operational support – a prominent role for decision-making. Another conclusion from our review is that research needs to come to more reliable predictions on which subsequent intervention decisions can be based. In essence, what is needed in our opinion, is research on the semi-automated selection of possible scenario-intervention pairs: Once data sensed from a crowd has been analyzed (mined) and predictions on its future have been made, it should, at least theoretically, be possible to suggest interventions for managing the crowd toward a desirable state. However, such suggestions are highly dependent on the context in which an observed crowd is considered. Subsequently, data is needed for studying similar situations on which new decisions could then be based. Such situations need to be recognized, i.e., described, searchable, and identifiable in an automated fashion. It is clear that much more research is needed to advance especially this part of the field.

To conclude, in order to address the shortcomings in research identified, our INCROWD framework makes two valuable contributions. First, it describes a high-level architecture for decision-support in crowd management. Second, by integrating the diverse crowd management tasks and stages with the necessary model development steps, we structure the field in a way that it becomes easier to identify where to focus scholarly attention.

Acknowledgments

This publication was supported by the Dutch national program COMMIT. We would like to thank Otto Adang and Frithjof Stöppler for their valuable feedback on earlier versions of this paper.

Appendix A. Review references

This appendix contains an overview of the 237 papers used in the survey. Each paper is referred to by a number throughout our status report on crowd research in section 6. For each paper number, the corresponding citation and reference can be obtained using Table A.7 and the references.

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Table A.7: Overview of the 237 papers included in our review: Number and reference.

nr reference	nr reference	nr reference	nr reference	nr reference	
1: [Abolghasemzadeh, 2013]	46: [Drury and Reicher, 2000]	91: [Johansson et al., 2008]	136: [Moore et al., 2008]	181: [Shiwakoti et al., 2014]	226: [Yu and Johansson, 2007]
2: [Adang, 2011]	47: [Drury and Reicher, 2005]	92: [Johnson and Feinberg, 1977]	137: [Moussaïd et al., 2009]	182: [Shiwakoti et al., 2015]	227: [Yuen and Lee, 2012]
3: [Aguirre et al., 1998]	48: [Drury et al., 2009]	93: [Johnson and Feinberg, 1997]	138: [Moussaïd et al., 2011]	183: [Siebel and Maybank, 2002]	228: [Zarboutis and Marmaras, 2007]
4: [Ahn et al., 2005]	49: [Durupinar et al., 2008]	94: [Kady, 2012]	139: [Muhdi et al., 2009]	184: [Silverman et al., 2002]	229: [Zhan et al., 2005b]
5: [Algadhi and Mahmassani, 1990]	50: [Dyer et al., 2008]	95: [Kang and Kim, 2005]	140: [Murakami et al., 2002]	185: [Silverman et al., 2006]	230: [Zhan et al., 2005a]
6: [AlGadhi et al., 2002]	51: [Fang et al., 2003]	96: [Kang, 2007]	141: [Muramatsu et al., 1999]	186: [Sime, 1983]	231: [Zhang et al., 2007a]
7: [Ali and Shah, 2007]	52: [Farenc et al., 2000]	97: [Khan and Shah, 2006]	142: [Muramatsu and Nagatani, 2000]	187: [Simonovic and Ahmad, 2005]	232: [Zhang et al., 2007b]
8: [Alizadeh, 2011]	53: [Feinberg and Johnson, 1988]	98: [King and Waddington, 2005]	143: [Musse and Thalmann, 1997]	188: [Smith et al., 2005]	233: [Zhao and Nevatia, 2004a]
9: [Andersson et al., 2009]	54: [Feinberg and Johnson, 1990]	99: [Kirchner and Schadschneider, 2002]	144: [Musse et al., 1999]	189: [Smith et al., 2009]	234: [Zhao and Nevatia, 2004b]
10: [Andrade and Fisher, 2005]	55: [Feinberg and Johnson, 1995]	100: [Kirchner et al., 2004]	145: [Musse et al., 2007]	190: [Song et al., 2006]	235: [Zhao et al., 2006]
11: [Andrade et al., 2006a]	56: [Feinberg and Johnson, 2001]	101: [Kong et al., 2006]	146: [Nakayama et al., 2005]	191: [Song et al., 2013]	236: [Zhao et al., 2008]
12: [Andrade et al., 2006b]	57: [Fraser-Mitchell, 1999]	102: [Kretz and Schreckenberg, 2006]	147: [Narain et al., 2009]	192: [Still, 2000]	237: [Zheng et al., 2010]
13: [Antonini et al., 2004b]	58: [Fridman and Kaminka, 2007]	103: [Kretz et al., 2006c]	148: [Narimatsu et al., 2004]	193: [Stott and Reicher, 1998]	238: [Zou et al., 2005]
14: [Antonini et al., 2004c]	59: [Fridman and Kaminka, 2010]	104: [Kretz et al., 2006a]	149: [Nguyen et al., 2005]	194: [Stott et al., 2008]	
15: [Antonini et al., 2004d]	60: [Fukamachi and Nagatani, 2007]	105: [Kretz et al., 2006b]	150: [Nishinari et al., 2006]	195: [Strogatz et al., 2005]	
16: [Aubé and Schield, 2004]	61: [Galea and Galparsoro, 1994]	106: [Lakoba et al., 2005]	151: [Notake et al., 2001]	196: [Tarnow, 1996]	
17: [Bae and Ryou, 2015]	62: [Goldenstein et al., 2001]	107: [Langston et al., 2006]	152: [Ozel, 2001]	197: [Tavares and Marshall, 2012]	
18: [Banarjee et al., 2005]	63: [Gotoh et al., 2012]	108: [Lee and Hughes, 2006]	153: [Pan et al., 2007]	198: [Teknomo and Fernandez, 2012]	
19: [Bandini et al., 2009]	64: [Graat et al., 1999]	109: [Lee et al., 2007]	154: [Paris et al., 2006]	199: [Thompson and Marchant, 1995b]	
20: [Batty et al., 2003b]	65: [Gupta and Yadav, 2004]	110: [Lee and Hughes, 2007]	155: [Parisi and Dorso, 2005]	200: [Thompson and Marchant, 1995a]	
21: [Batty et al., 2003a]	66: [Harada et al., 2015]	111: [Leggett, 2004]	156: [Parisi et al., 2015]	201: [Toner and Tu, 1998]	
22: [Bellomo and Dogbe, 2008]	67: [Helbing, 1991]	112: [Leibe et al., 2005]	157: [Pathan et al., 2010]	202: [Treuille et al., 2006]	
23: [Berk, 1974]	68: [Helbing, 1992]	113: [Lerner et al., 2007]	158: [Pauls, 1984]	203: [Tucker et al., 1999]	
24: [Blue and Adler, 1999]	69: [Helbing and Molnar, 1995]	114: [Li et al., 2015]	159: [Pelechano et al., 2005]	204: [Ulicny and Thalmann, 2002]	
25: [Blue and Adler, 2001]	70: [Helbing and Molnar, 1998]	115: [Li and Han, 2015]	160: [Pelechano and Badler, 2006]	205: [Varas et al., 2007]	
26: [Bo et al., 2007]	71: [Helbing et al., 2000]	116: [Liao et al., 2014]	161: [Pelechano et al., 2007]	206: [Venuti and Bruno, 2007]	
27: [Boghossian and Velastin, 1999]	72: [Helbing et al., 2002]	117: -	162: [Pereira et al., 2013]	207: [Venuti et al., 2007]	
28: [Borrmann et al., 2012]	73: [Helbing et al., 2005]	118: [Lin et al., 2007]	163: [Piccoli and Tosin, 2009]	208: [Villamil et al., 2003]	
29: [Braun et al., 2003]	74: [Helbing et al., 2007]	119: [Lo and Fang, 2000]	164: [Piccoli and Tosin, 2011]	209: [Vu et al., 2002]	
30: [Brostow and Cipolla, 2006]	75: [Heliövaara et al., 2012]	120: [Lo et al., 2004]	165: [Pires, 2005]	210: [Wang et al., 2015]	
31: [Camillen et al., 2009]	76: [Henderson, 1971]	121: [Lo et al., 2006]	166: [Proulx, 1993]	211: [Was, 2005]	
32: [Cepolina, 2005]	77: [Henderson, 1974]	122: [Løvås, 1994]	167: [Qu et al., 2014]	212: [Weifeng et al., 2003]	
33: [Chow and Ng, 2008]	78: [Henderson and Jenkins, 1974]	123: [Lovreglio et al., 2014]	168: [Rahmalan et al., 2006]	213: [Weifeng and Hai, 2007]	
34: [Colombo and Rosini, 2005]	79: [Henein and White, 2005]	124: [Luo et al., 2008]	169: [Reicher, 1996]	214: [Wijermans et al., 2013]	
35: [Courty and Raupp Musse, 2005]	80: [Henein and White, 2007]	125: [Ma et al., 2012]	170: [Reisman et al., 2004]	215: [Wong and Luo, 2005]	
36: [Courty and Corpetti, 2007]	81: [Hoogendoorn and HL Bovy, 2003]	126: [Mahadevan et al., 2010]	171: [Rodriguez et al., 2011]	216: [Wong and Cheung, 2006]	
37: [Cupillard et al., 2002]	82: [Hoogendoorn and Bovy, 2004]	127: [Marana et al., 1998b]	172: [Roggen et al., 2011]	217: [Wu and Huang, 2015]	
38: [Davidich and Köster, 2012]	83: [Huang et al., 2009]	128: [Marana et al., 1998a]	173: [Saiwaki et al., 1999]	218: [Xiong et al., 2007]	
39: [Davies et al., 1995]	84: [Hughes, 2000]	129: [Marana et al., 1999]	174: [Sakuma et al., 2005]	219: [Georgoudas et al., 2006]	
40: [Dijkstra et al., 2001]	85: [Hughes, 2002]	130: [Marconi and Chopard, 2002]	175: [Schadschneider et al., 2002]	220: [Yamamoto et al., 2007]	
41: [Ding, 2011]	86: [Hughes, 2003]	131: [Marques et al., 2003]	176: [Schubert and Suzic, 2007]	221: [Yang et al., 2005]	
42: [Dombroski et al., 2006]	87: [Hussain et al., 2011]	132: [Martella et al., 2013]	177: [Schwarz and Mosler, 2005]	222: [Yang et al., 2012]	
43: [Dong et al., 2007]	88: [Isobe et al., 2004]	133: [McKenna et al., 2000]	178: [Seyfried et al., 2005]	223: [Yaseen et al., 2013]	
44: [Drews et al., 2010]	89: [Jager et al., 2001]	134: [Mehran et al., 2009]	179: [Shen, 2006]	224: [Yin et al., 1996]	
45: [Drury and Reicher, 1999]	90: [Jiang et al., 2009]	135: [Mittal and Davis, 2002]	180: [Shi et al., 2012]	225: [Yu et al., 2005]	