Integrating Social Media in Emergency Dispatch via Distributed Sensemaking

Rob Grace
Penn State University
wrg123@ist.psu.edu

Shane Halse
Penn State University
seh297@ist.psu.edu

Jess Kropczynski
University of Cincinnati
jess.kropczynski@uc.edu

Andrea Tapia
Penn State University
atapia@ist.psu.edu

Fred Fonseca
Penn State University
ffonseca@ist.psu.edu

ABSTRACT

Emergency dispatchers typically answer 911 calls and relay information to first responders; however, new workflows arise when social media analysts are included in emergency dispatch work. In this study we examine emergency dispatch workflows as distributed sensemaking processes performed among 911 call takers, dispatchers, and social media analysts during simulated emergency dispatch operations. In active shooter and water rescue scenarios, emergency dispatch teams including call takers, dispatchers, and social media analysts make sense of unfolding events by analyzing, aggregating, and synthesizing information provided by 911 callers and social media users during each scenario. Findings from the simulations inform design requirements for social media analysis tools that can help analysts detect, seek, and analyze information posted on social media during a crisis, and protocols for coordinating analysts' sensemaking activities with those of 911 call takers and dispatchers in reconfigured emergency dispatch workflows.

Keywords

sensemaking, emergency dispatch, social media, simulation

INTRODUCTION: INTEGRATING SOCIAL MEDIA IN NEXT-GENERATION EMERGENCY DISPATCH

When someone dials an emergency telephone number like 911, they begin an information processing task that culminates when a first responder arrives at the scene of an emergency. While information dispatched to first responders (i.e. fire, medical, police) constitute the output of this task, the inputs, traditionally provided by 911 callers, are increasing in volume and variety. The development of Next-Generation 911 infrastructure will soon allow people to call, text, or use web-based applications to contact emergency dispatch centers (Holland, 2018), known as Public-Safety Answering-Points (PSAPs), which, increasingly, seek to detect emergencies and gather situational awareness information using data collected from physical and social sensors, including social media.

In the new, data-rich PSAP, the work of emergency dispatchers coordinating information flows between citizens and first responders— the throughput of emergency response— becomes much more complex. Anticipated by data analytics in policing beginning with early statistical tools such as CompStat in New York City and, more recently, dedicated Strategic Decision Support Centers in Chicago (Smith, 2018), PSAPs are beginning to process an array of data inputs from physical (e.g. cameras, license plate readers, and gunshot detectors) and social (e.g. 911 calls and social media) sensors, and digital records databases (e.g. arrests, complaints, summonses, and firearm registries) (Levine & Tisch, 2014). Consequently, PSAPs are transforming from reactive call centers to proactive data analytics and coordination hubs providing first responders with real-time information before, during, and after emergencies.

In this regard, integrating social media in emergency dispatch operations presents PSAPs with distinct opportunities. PSAPs can use social media to disseminate warnings and other emergency-related information during crises when call processing may be disrupted or delayed due to high-call volumes. Utilized for situational awareness, social media can alert PSAP staff to developing emergencies and augment information provided by 911 callers (Grace, Kropczynski, & Tapia, 2018). While prior studies examine the coordination of emergency dispatch work surrounding traditional call taking and dispatch activities (Furniss & Blandford, 2006; Norri-Sederholm, Seppälä, Saranto, & Paakkonen, 2016; Preusse & Gipson, 2016), Boersma et al. (2016) describe the novel trial of Twitcident, a web-based system for filtering, searching, and analyzing social media data within Dutch emergency dispatch centers. The trial proved "disappointing" as dispatchers had trouble selecting search terms to filter social media data as well as difficulty integrating information from social media and existing information sources. As a result, the system often provided redundant information that did not enhance emergency dispatch operations (p. 243-4). The findings of Boersma et al. suggest that integrating social media in emergency dispatch requires, first, developing social media analysis tools that can provide dispatchers-turned-analysts with relevant information and, second, integrating social media monitoring within emergency dispatch workflows already responsible for gathering and integrating information from multiple 911 callers.

Consequently, this study examines how PSAPs can incorporate social media analysts and social media analysis tools within workflows integrating information from social media and 911 calls during an emergency. We approach these workflows as distributed sensemaking processes performed among 911 call takers, dispatchers, and social media analysts. Whereas prior studies examine sensemaking among social media users posting and engaging social media content during a crisis (Mirbabaie & Zapatka, 2017; Stieglitz, Mirbabaie, & Milde, 2018), or among officials gathering information only from emergency callers (McMaster, Baber, & Duffy, 2012), this study explores how emergency dispatch teams make sense of events during an emergency by analyzing, aggregating, and synthesizing information from social media and 911 calls to address the evolving situational awareness needs of first responders. Conducting simulations to explore new workflows and distributed sensemaking processes of emergency dispatch teams in active shooter and water rescue scenarios, the findings of this study inform design requirements for social media analysis tools that can help analysts detect, seek, and analyze information posted on social media during a crisis, and protocols for coordinating analysts' sensemaking activities with those of 911 call takers and dispatchers in reconfigured emergency dispatch workflows.

THEORY: EMERGENCY DISPATCH AS DISTRIBUTED SENSEMAKING

Following Klein et al. (2007), we approach sensemaking as "a deliberate effort to understand events" (p. 114). Figure 1 illustrates the Data-Frame model of sensemaking, an iterative process of modifying or replacing the current understanding of a situation or "frame." According to Klein et al. (2007), a frame is "an explanatory structure that defines entities by describing their relationship to other entities" (p. 118). Frames can take the form of stories, maps, or scripts (p. 118). Stories provide chronological orderings and causal relationships, while maps provide spatial arrangements from which routes to landmarks can be inferred. Scripts, in contrast, outline cooperative roles and coordinate action by meshing together actors' activities. Importantly, frames both explain a situation and guide information seeking: "a frame is a structure for accounting for the data and guiding the search for more data" (p. 118).

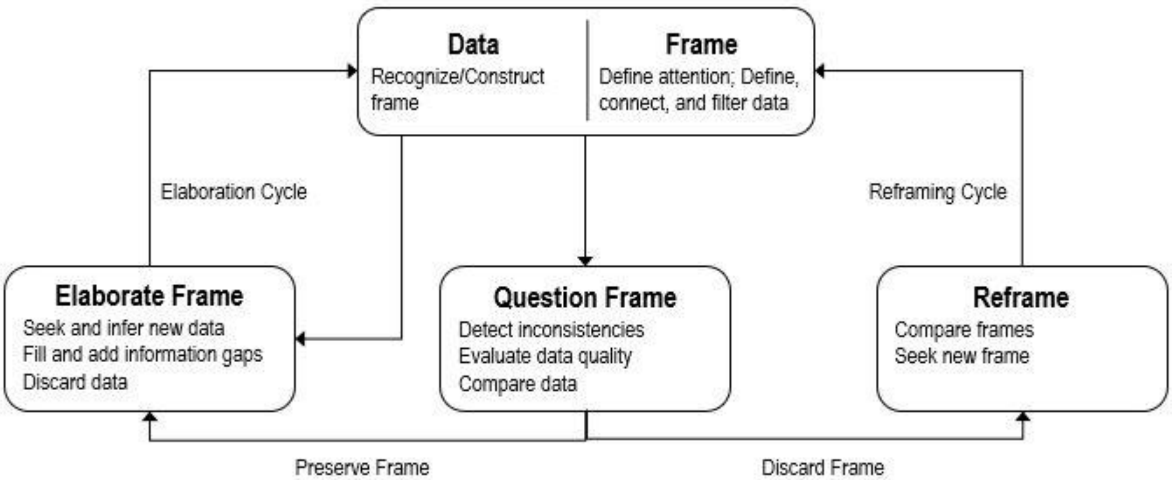

Figure 1. Four Functions of Sensemaking Cycle (Klein et al., 2007)

Shown in Figure 1, sensemaking develops within a frame (A) providing understanding of the situation at hand, to include gaps in understanding that can be addressed by seeking further information. When encountering a new situation, actors can infer frames using only a few data points referred to as "cues" (Weick, Sutcliffe, & Obstfeld, 2005) or "anchors" (Klein et al., 2007): "the initial one or two key data elements we experience sometime serve as anchors for creating an understanding. These anchors elicit the initial frame, and we use that frame to search for more data elements" (p. 122). Incorporating social media in emergency dispatch requires understanding the repertoire of explanatory frameworks (i.e. frames) dispatchers use to interpret and seek information on social media, as well as the characteristics of social media data (i.e. cues) that facilitate analysis and information seeking (McMaster et al., 2012). To examine how dispatchers use frames in the context of emergency dispatch work, we therefore ask: *(RQ1) How do dispatchers analyze social media data within emergency dispatch workflows?*

The existing frame is elaborated (B) when new information is discovered that provides additional details about the situation. The elaboration loop in Figure 1 represents the process of seeking information to fill (or identify) information gaps and establish new relationships among newly-discovered and existing information characterizing the frame. Incorporating social media in emergency dispatch requires understanding a distributed process of elaboration in which call takers, analysts, and dispatchers seek, analyze, and integrate information from multiple data sources in ways that add to the collective understanding of an emergency. To examine how dispatchers discover new details and elaborate existing frames, we therefore ask: *(RQ2) How do dispatchers search social media data and integrate information from social media and 911 calls?*

Encountering inconsistent data calls into question (C) the existing frame, which can either be preserved and elaborated (to include discarding anomalous data), or reframed (D) by selecting a new frame. These encounters are critical insofar as they allow us to recognize errors and adjust our understanding of dynamic events. As dispatchers use information gathered from social media users and 911 callers to understand evolving emergency events, we ask: *(RQ3) How do dispatchers discover inconsistencies among information from social media and 911 calls?* Moreover, when information about an emergency (e.g. where, what, who) varies among social media posts and 911 calls, dispatchers must compare multiple, incomplete, and inconsistent reports across data sources and determine whether the information provides new details about a known emergency (i.e. elaboration), redundant information (i.e. preservation), or identifies a hitherto unreported emergency (i.e. reframing). Therefore, and lastly, to examine how dispatchers evaluate inconsistent information, we ask: *(RQ4) How do dispatchers determine if information from social media is supplemental, redundant, or novel?*

METHOD: EMERGENCY DISPATCH SIMULATIONS

This study reports findings from scenario-based emergency dispatch simulations conducted at a large, urban PSAP which processes approximately 3000 calls a day. The simulations were organized to provide the PSAP with procedural and technological requirements for incorporating social media in its emergency dispatch operations. Drawing on role play methods in interaction design, the simulations involved participating dispatchers performing the roles of call taker, dispatcher, and social media analyst in a constructed scenario (Medler & Magerko, 2010; Svanaes & Seland, 2004). Widely used in human-centered design, role playing allows researchers to observe plausible interactions among domain-experts and prospective end-users as they develop within hypothetical situations (Medler & Magerko, 2010), especially emergency situations which are difficult to directly observe and inappropriate for research activities (Valkonen & Liinasuo, 2010). The simulations involved six dispatchers performing in teams including a call taker, dispatcher (participants' professional duties in the PSAP), and social media analyst (new specialization under consideration by PSAP administrators), tasked with processing information from synthetic 911 caller and social media datasets using a simulated Computer-Aided Dispatch (CAD) system and analytic dashboard during two mock emergency scenarios.

During a prior workshop held at the PSAP in May 2018, researchers conducted activities with six dispatchers and 25 first responders (fire, medical, and police) to inform the design of two scenarios and associated synthetic social media and 911 call datasets. The workshop involved two activities. First, dispatchers and first responders composed "golden tweets," examples of social media posts that would support situational awareness needs of first responders (blinded for review). Discussed among the examples were golden tweets based on a mall shooting encountered by the PSAP the year prior. These motivated the creation of the *mall shooting dataset*, consisting of 20 emergency-related tweets, four mock 911 calls, and 1000 tweets collected for Charleston County on March 19th, 2018 from 4-6pm (as background noise). Second, sets of 50 weather-related tweets were provided to first responders to sort into piles of "actionable" and "non-actionable" information. The tweets were collected for Charleston County on April 15th, 2018 when the PSAP experienced high call volumes during a severe storm that caused flooding throughout the area. Using the sorted tweets and flood-related golden tweets, researchers created the *severe flooding dataset*, consisting of three emergency-related tweets, 1000 "noise" tweets collected on April 15th, and six mock 911 calls. Importantly, and inspired by our discussions with dispatchers and first responders, the mock tweets and 911 calls in both datasets provide incomplete information (e.g. "what" without "where" information), and therefore required dispatchers to compare and integrate information across these reports to support the situational awareness needs of first responders during each scenario.

Taking place during a follow-up workshop in August 2018, the simulations mimicked a live emergency environment by placing the participating dispatchers in the auxiliary dispatch room of the PSAP in which the call taker, analyst, and dispatcher took up individual workstations and interacted asynchronously via text-based communication using the simulated CAD environment. The analyst was additionally provided with an analytic dashboard (Toepke, 2018), which included a map to examine geotagged tweets, tweet filtering and visualization using search terms, and word cloud displaying trending hashtags that could be individually selected to visualize associated tweets on the map and tweet list displays (Figure 2). A researcher with an audio recorder was present at each workstation where talk-aloud methods were employed to collect data from the call taker, analyst, and dispatcher as they processed calls or analyzed social media data during each scenario (Jaspers, Steen, Van Den Bos, & Geenen, 2004). The participant in the role of call taker communicated directly with the 911 caller (research confederate) and talked aloud with a researcher while entering information in the simulated CAD. Using activities of the sensemaking cycle- framing, elaboration, questioning, and reframing- as sensitizing concepts, researchers coded the transcribed audio recordings and textual data participants entered in the simulated CAD environment (Strauss, 1987). The researchers discussed and iteratively refined the coded data to address emergent aspects of the distributed sensemaking process, for instance, the use of cues and search heuristics among dispatchers when searching and filtering tweets during each scenario.

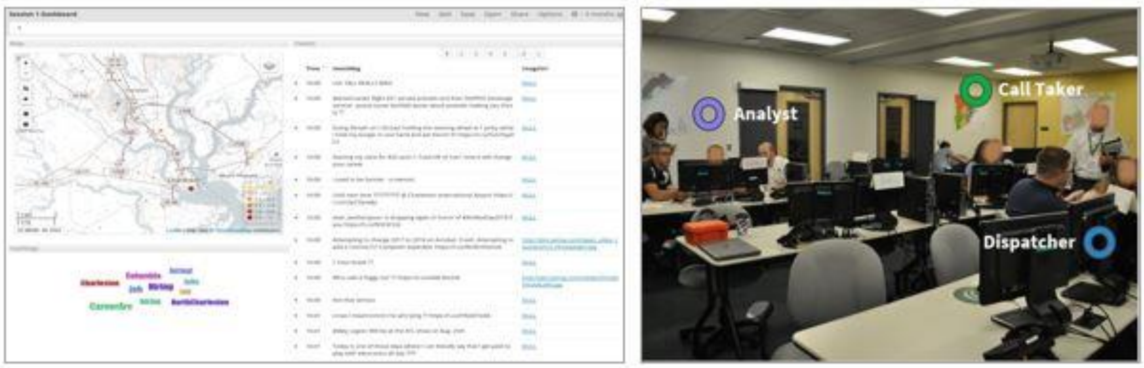

Figure 2. Social media analytics dashboard (left) used in simulations with mock CAD workstations (right)

ANALYSIS: MALL SHOOTING AND FLOODING SCENARIOS

For simulation scenario, a synopsis describes the actions performed by the call taker, dispatcher, and social media analyst, while annotations (*in italics)* associate these distributed activities with sensemaking activities of framing, elaborating, questioning, and reframing. The following discussion analyzes these sensemaking functions in detail by drawing on data collected as call takers, dispatchers, and, especially, social media analysts, explained aloud their actions during each scenario.

Scenario One: Mall Shooting

Scenario one begins when a 911 caller reports gunshots at Citadel Mall and, simultaneously, a dashboard alert identifies tweets describing a "shooting" (Table 1). The dispatch team next processes two additional 911 calls and multiple tweets reporting information on wounded victims, survivors sheltered in place throughout the mall, and the description and whereabouts of the suspect(s). Framing the Emergency using Primary Cues

Alerted that "shooting" had been tweeted, the analyst employs the word as a search term to identify three tweets reporting an emergency:

> #citadellMall #shooting Hiding in Journeys @NCPD 3 people here not injured @CCSO
>
> There are people running and screaming in the mall. Someone is shooting
>
> Shooting at citadel mall in Food Court. Shooter in just walked out

The call taker simultaneously answeres a 911 call describing "loud pops, like someone is shooting here...People were screaming and just running out of the store." Based on primary information cues (e.g. "Citadel Mall," "shooter," "loud pops"), the call taker and analyst recognize the incident type and location, and quickly enter calls 1-2 for an "active assailant" at Citadel Mall. By establishing the primary information necessary to dispatch a response (i.e. where and what), the call taker and analyst contribute to the emergency frame that will guide information seeking and integration among the call taker, analyst, and Dispatcher throughout the duration of the scenario.

Elaboration by Seeking Secondary Information

Next, the analyst searches for secondary information (e.g. weapons, who, when, why) that will support situational awareness among first responders now en route to the scene. Importantly, the emergency frame functions as a story, providing dispatchers with a likely order of events taking place at Citadel Mall, as well as a set of corresponding information requirements:

> For the initial response I want to know who the suspect is and what they look like and where they go… several people have reported that they've ran away so did they run out of the food court, did they run out of where? Did they get into a car? Everything about the suspect.
>
> Once the suspect issue has been dealt with by the police department, then… they can find out where the victims are… From there we would go into where people are sheltered in place. So suspect information first, then where the victims are, and then the sheltered in place. (Analyst, Scenario 1)

The emergency frame, in this case an active assailant incident at Citadel Mall, prioritizes situational awareness (i.e. secondary information) requirements to guide information seeking between the call taker and analyst as they search for new information and, ostensibly, dispatch information first responders need when they need it.

Table 1. Four phases of mall shooting scenario

Call Taker	Answers 911 call: "I'm outside Citadel Mall and there are loud pops like someone is shooting here. I just ran out of target and am driving away…" Enters an active assailant call (2) into CAD *[Framing: Active Assailant]*, and notes that there is no further information on potential suspects or injuries. *[Elaboration: Information gap]*
Analyst	Alerted to tweets describing a "shooting," searches and identifies three tweets and opens a call (1) for an active assailant in CAD *[Framing: Active Assailant]*: "several tweets reporting active shooter at the mall, one person reports near the food court and suspect is possible gone on arrival...one person reports 3 survivors sheltered in place in Journeys, negative injuries with this report." *[Elaboration: Survivors, Information gap]*
Dispatcher	Combines information entered by the call taker and analyst for dispatch (Call 1,2). Sends an alert tone for emergency units to respond to an active assailant incident in progress; begins to provide situational updates to first responders.
Analyst	Searches map; identifies geotagged tweet reporting injuries and enters additional call notes (1) in CAD: "multiple shot near food court and shooter is gone on arrival, no descriptions or specific locations of victims or suspect." *[Elaboration: Victims, Information gap]*
Dispatcher	"One party advising incident occurred near food court, suspect possibly gone on arrival, one party reporting three people sheltered in place at Journeys. Negative injuries reported at this time" (Call 1).
Call Taker	A second call comes in: "I'm in a back room in the store Belk. Someone is shooting and we are hiding here. There are three of us…" Enters a new call (3): "shots coming from inside the mall, poss. not in Belk; negative on any suspect information; negative on any known injuries; weapon unknown." *[Framing: Active Assailant; Elaboration: Information Gap]*
Analyst	Uses the search term "Belk" to discover reports of shots fired near the department store. Compares this information with call notes entered in CAD (3), and concludes the information is redundant. *[Questioning: Preserve frame (discard data)]*
Dispatcher	"Notification that there are still shots fired at this time, use caution. one caller advising they and two others are in Belk storage rooms sheltering in place… still no suspect info" (Call 3).
Call Taker	Another call (4): "I am outside Belk in the parking lot… I think there are two white guys with guns… Lots of people are running through the parking lot…" Makes further entries into CAD: "Parking lot outside of Belk; two white males, negative on clothing, unknown further; caller on the line, pending more suspect information." *[Elaboration: Suspects]*
Dispatcher	"Be advised, two white male suspects, armed, reported in the Belk parking lot" (Call 4). Requests further information from the call taker still speaking with the 911 caller: "...which parking lot of Belk?"

In the scenario, however, this never happens. The analyst adopts ineffective search terms and fails to discover most of the suspect information available in the tweet dataset during the scenario, notably:

> I'm locked in the women's room. There's a tall skinny white guy in blue jeans and a white tshirt.
>
> man with a gun just got into a red SUV and turned right on Orleans Rd
>
> shirtless man with assault rifle running to car outside the mall [picture of shirtless man next to a red SUV]

During both scenarios, analysts rely on search heuristics employed as 911 call takers, but which prove ineffective when adapted to filtering social media data (i.e. poor recall). Explaining that he has “seen a lot of people using the business name versus an address or road name,” the analyst uses the department store name “Belk” referred to by an earlier 911 caller (Call 3). Relying on cues provided by 911 callers, analysts adopted similar heuristics, typically using the names of businesses or other geographic landmarks, to search generally for emergency-related information.

Consequently, analysts did not select search terms associated targeting specific, priority information. Instead, analysts provided information for dispatch as discovered, such as when the analyst provided information on survivors sheltered in place (Call 1) early in the response when suspect and victim information remained priorities. By using search terms explicitly provided by 911 callers or alerts provided by the analytic dashboard, the analyst reactively filtered social media data in ways that often proved ineffective at identifying and triaging priority information.

Elaboration by Identifying Gaps in Situational Awareness

Whenever entering new information into CAD, the call taker and analyst also described what information remained unknown: “negative injuries with this report” (Call 1), “unknown any injuries… no suspect information” (Call 2), “negative on any suspect information; negative on any known injuries; weapon unknown” (Call 3), “negative on clothing, unknown further” (Call 4). By identifying information gaps in CAD, the call taker and analyst support shared awareness among dispatchers and first responders during the response:

> When we got the additional tweet of multiple people shot, I went back to the original [call] notes I had [for Call 1] to report multiple people shot near the food court... the shooter is gone, and... that there are no descriptions or specific locations because some of these officers are going to ask for that. I know they are going to ask for that so I go ahead and tell them there is nothing more specific. (Analyst, Scenario 1)

Information gaps can be determined with respect to secondary information associated with the emergency frame: an active assailant at Citadel Mall. In scenario one, missing information included descriptions of weapons, the shooter, as well as potential victims and survivors sheltering in place. As previously described, however, the analysts’ inflexible search heuristics precluded targeted information seeking to address information gaps articulated among the dispatchers.

Questioning and Discarding Redundant Information

In phase three of the scenario, the call taker enters a call (3) from a survivor sheltering in place in Belk, a department store in Citadel Mall. The analyst subsequently uses the search term “Belk” and identifies two tweets reading “loud pops near Belk in the mall. Sounds like a gun people running screaming” and “In Belk 🙏🙏🙏 #help #pray #charleston.” The analyst compares this information to existing information entered in CAD and already dispatched to first responders:

> I searched for “Belk.” I had one [tweet] pop up basically reporting what sounds like pops, or a gun going off… There is no additional information I can pull out of that. They already know there is a shooting at the mall near Belk, they already know people are running around and screaming. It’s an active shooter incident. So, there is nothing additional I can pull from here to put into there… It’s redundant information because everything that is here is already here [in CAD]. (Analyst, Scenario 1)

Although the tweets provide information related to the emergency, the analyst does not consider them relevant in the situation given the information already available and the evolving information requirements of the response. From a sensemaking standpoint, the phase illustrates the analyst questioning encountered information to gauge its quality with respect to information characterizing the existing frame. Concluding the former corroborates the frame without providing any new information for its elaboration, the analyst discards the data.

Scenario Two: Severe Flooding

Scenario two involves roadway flooding in different locations causing traffic hazards and the need for two water rescues. Table 2 provides a synopsis of the role play in three phases.

Discovering Inconsistencies among Information from Social Media and Emergency Callers

As in scenario one, the analyst did not readily discover information during each emergency, to include the discovery of inconsistencies among information that might lead to a reframing of awareness. In phase two, for instance, the analyst enters a call for a traffic hazard on Harbor View Boulevard after searching “flooding” and discovering a tweet reporting flooding on Harbor View near Harris Teeter, a supermarket. What the analyst did not discover, however, was a tweet requesting a water rescue in the same location:

> So much water at Lake Francis near CVS. Rd. impassable. ONE PERSON STUCK IN CAR.

Lake Francis Drive intersects with Harbor View Boulevard immediately across from the shopping center parking lot in which both Harris Teeter and CVS, a pharmacy, are located. The analyst later discovers this tweet by accident when searching for “Pier One” after the store name was mentioned by a 911 caller reporting flooding eight miles away on Sam Rittenberg Boulevard- an unrelated incident. That the search results for “Pier *One*” returned a tweet reporting “*One* person stuck in a car” was purely serendipitous.

Table 2. Three phases of flooding scenario

Call Taker	Enters a call (1) into CAD when someone reports roadway flooding near the Dollar General on Camp Road. *[Framing: Traffic Hazard]*
Analyst	After checking tweets appearing on the map, then searching for “Dollar General” and “flooding,” discovers tweet reporting a trapped person at the intersection of Dills Bluff and Camp Road. Determines this a distinct incident and enters a call (2) into CAD. *[Questioning: Inconsistent location; Reframing: Water Rescue]*
Dispatcher	Uses radio to dispatch a police unit to Camp Road (1), and then police, fire, and medical units to the Dills Bluff incident (2), noting: “units dispatched to both sides of the roadway to set up cones and Traffic and Transportation notified [of lane closures].”
Analyst	Also discovered when searching for “flooding,” a tweet shows an image of flooding in the parking lot of Harris Teeter. Enters a call (3) into CAD. *[Framing: Traffic Hazard]*
Dispatcher	Dispatches a police unit to the Traffic Hazard near Harris Teeter (3) and asks the analyst to clarify the depth of the water in the tweeted picture: “what is a 4-5 drop zone?”
Call Taker	Another call arrives reporting more roadway flooding, this time near Pier One Imports on Sam Rittenberg Road. Enters another call (4) for a Traffic Hazard into CAD. [*Framing: Traffic Hazard*]
Analyst	Searching “Pier One,” finds tweet reading “So much water at Lake Francis near CVS. Rd. impassable. ONE PERSON STUCK IN CAR.” Determining that the CVS is in the same parking lot as the Harris Teeter, enters call notes (3) requesting a Water Rescue. *[Questioning: Inconsistent location; Reframing: Water Rescue]*
Dispatcher	Dispatches police to Traffic Hazard on Sam Rittenberg and uses CAD to ask the call taker if anyone is in the vehicles. “Caller did not advise,” answers the Call taker. Dispatches units to a water rescue. In call notes (3) the dispatcher writes, “Copy, duplicating call for emergency Fire Rescue (EFR). Confirming information with police department on the scene.”

As the example illustrates, the types of cues provided by 911 callers and entered into CAD by call takers condition analysts’ discovery of emergency-related information. The previous example also illustrates the difficulty of discovering an emergency when no one calls 911; the initial call entered into CAD for a traffic hazard on Harbor View near Harris Teeter was entered earlier by the analyst after discovering a picture of the flooding on Twitter. That the analyst was not initially aware of the trapped person at the Harborview and Lake Francis intersection demonstrates, again, the difficulty of discovering unknown information about an unknown emergency.

Evaluating Inconsistencies among Information from Social Media and 911 Callers

Searching and filtering tweets, however, constitutes only the first step of integrating information from social media within 911 dispatch operations. Next analysts must compare newly-obtained information from social media displayed on the dashboard interface with existing, integrated information from 911 callers and social media displayed on CAD and shared among the call taker, dispatcher and analyst. At this stage inconsistencies appear when analysts cannot not determine if a discovered tweet(s) reports a new emergency not yet entered into CAD, new situational awareness information for a reported emergency, or redundant information about an already-reported emergency.

Consequently, the ability of analysts to evaluate inconsistencies among information displayed on the analytic dashboard, and between information displayed on the dashboard and CAD, becomes critical to effectively integrating information from social media and 911 callers for emergency dispatch. In phase one, for example, the analyst must determine if the trapped person at the intersection of Camp Road and Dills Bluff is related to the flooding earlier reported on Camp Road (near the Dollar General) by a 911 caller. Comparing the available location information for each incident, the analyst determines them to be separate and therefore enters a new call into CAD for a water rescue, rather than adding additional information to the existing call for the traffic hazard.

To do this, however, the analyst uses primary information cues in the tweets, words that indicate the incident type and location of the emergency. When asked to consider a likely counterfactual, if the tweet had provided less detailed location information by omitting reference to Dills Bluff, the analyst describes *how* dispatchers evaluate and compare inconsistent information from multiple emergency reports:

> If this Dills Bluff thing wasn't here, and it just said lots of flooding on Camp Road, my car's flooded, I need a boat, [then] flooding on Camp Road is related to the Dollar General on Camp Road where there is a lot of flooding reported. I would add it to the same call then. However, because there is this specific location, I would probably create an entirely separate call. (Analyst, Scenario One)

Lacking the primary cue "Dills Bluff," and therefore presented with less exact location information, the analyst would infer that the traffic hazard and water rescue are colocated- both on Camp Road near Dollar General- and refer to the same roadway flooding. However, when presented with more detailed location information, the analyst concludes that the incidents are distinct, occurring at different locations along Camp Road.

The analyst is working with protocols for dispatching a response that require classifying an incident type- in this case a water rescue- and an exact location. If the cue "Dills Bluff" was omitted by the social media user or not presented to the analyst, only the Camp Road at Dollar General location would meet this latter criterion. From a sensemaking perspective, the example illustrates how the analyst relies on cues in data to either elaborate an existing frame (Camp Road at Dollar General) or construct a new frame using cues sufficient to classify an exact location (Camp Road at Dills Bluff). Importantly, the analyst relies on the bottom-up presentation of cues available in the data and, at the same time, the top-down recognition of sensemaking frames from the repertoire of locations available for dispatch in Charleston County.

Similarly, in phase three, when the analyst serendipitously discovers the tweet requesting a water rescue on Lake Francis Boulevard near CVS, he must still evaluate the tweet in comparison to inconsistent information entered into CAD for dispatch:

> So when I was looking for Pier One there weren't any geotagged tweets from the area [on the map] but it looks like there are additional ones that popped up [in the tweet search]. I found one tweet here, "water at Lake Francis near CVS, road impassable, one person stuck in the car." So now I would identify where this is, looking up Lake Francis, looking up some of the CVSs trying to figure out where this was. (Analyst, Scenario 2)

The report of someone trapped in their car near Lake Francis near CVS is not immediately intelligible as the same location as the traffic hazard on Harbor View near Harris Teeter. Both roadways are long thoroughfares, and there are multiple chain supermarkets and pharmacies with the same name in Charleston.

To compare this new information with that already entered into CAD, the analyst again looks to primary information cues in the tweet that allow dispatchers to classify information for emergency dispatch:

> I can use the CAD system to determine where is Harris Teeter, where is Lake Francis, and where is the CVS near Lake Francis.... I would just look for Lake Francis Drive and see if I could find a CVS near there, and then compare this report to the CAD to see if there was a call already entered and, if not, then I would go ahead and enter one for water rescue. So they wouldn't be getting much information but they would be getting enough for a location and a basic response for one person stuck in a car due to possible flooding. (Analyst, Scenario 2)

Using the names of roadways and stores as primary cues, the analyst uses mapping applications (typically integrated in CAD) to classify the location of the emergency and determine if an emergency has already been reported in the same location. In this situation, the analyst determines that the newly-reported water rescue, and the already-dispatched traffic hazard are colocated: "if this is the same location...the person stuck in the water in the car is due to the flooding, basically" (Analyst, Scenario 2).

DISCUSSION: INTEGRATING SOCIAL MEDIA VIA DISTRIBUTED SENSEMAKING

In contrast to prior studies which examine sensemaking among social media users posting and engaging social media content during a crisis (Mirbabaie & Zapatka, 2017; Stieglitz et al., 2018), or among officials gathering information from emergency callers (McMaster et al., 2012), this study examines how emergency dispatchers make sense of information gathered from social media and 911 calls to address evolving situational awareness needs during an emergency. Importantly, this study examines sensemaking as a distributed process performed among emergency dispatch teams including existing (call takers and dispatchers) and future (social media analysts) specializations. Findings from the emergency dispatch simulations described in this study point to design requirements for social media analysis tools that can help analysts make sense of social media data created during an emergency, and protocols for coordinating analysts' sensemaking activities within emergency dispatch workflows capable of processing heterogeneous data to create actionable information.

Analyzing Information from Social Media and 911 Calls: Framing the Emergency

The simulations demonstrate how emergency dispatch teams make sense of information gathered from social media and 911 calls in sequences of sensemaking activities, or sensemaking workflows, which process and integrate information from heterogenous information sources to address the evolving situational awareness needs of first responders during an emergency. Drawing on Klein et al. (2006; 2007), this study observes four sensemaking activities constituting sensemaking workflows: framing, elaborating, questioning, and reframing. For each sensemaking activity, this study points to design implications for social media analysis tools that can help analysts make sense of social media data and protocols for coordinating analysts' sensemaking activities in workflows performed among emergency dispatch teams (Table 3).

Table 3. Design requirements supporting sensemaking by social media analysts

(Re)Framing	Cue Filtering	Identification and visualization of 6W cues in social media posts
	Domain Ontology	Incident determinant codes and information requirements (6Ws)
	COP	Situational awareness of calls and responding units
Elaborating	Assisted Search	6W-based classifiers to discover targeted information
	IS Protocols	SOPs to proactively address information gaps
Questioning	Alerts	Notifications to initiate sensemaking
	6W Visualizations	Visualizations contrasting 6W cues to reveal inconsistencies

The first activity, framing, sees dispatchers-turned-analysts make sense of social media data as they would 911 calls: associating data cues with a frame(s) explaining the situation. To analyze cues in social media data, analysts draw on the repertoire of frames commonly referred to as the "6Ws": Where, What, Weapons, Who, When, and Why (Kropczynski et al., 2018). The 6Ws represent a domain ontology organizing emergency dispatch work in which determinant codes representing classes of emergencies (i.e. what) are defined by attributes (i.e. where, weapons, who, when, why) with a set of possible values (e.g. street address in jurisdiction). Thus, analysts frame cues such as "loud pops," "shooting," and "Citadel Mall" with a determinant code indicating the class of emergency (e.g. 136E-1: Active Assailant) and a street address (e.g. 2070 Sam Rittenberg Blvd, Charleston, SC 29407). Thus, for analysts, effectively analyzing social media requires social media analysis tools that can filter information whose relevance is defined by the presence of cues enabling analysts to classify the attributes of an emergency (Kropczynski et al., 2018; Zade et al., 2018).

Framing practically involves entering a "call" in CAD whose primary information includes the "where" and "what" associated with an emergency, the minimum information required to dispatch emergency units. Highlighting the role of artifacts as frames (McMaster et al., 2012), and paired with the 6Ws domain ontology, calls displayed in CAD create a Common Operating Picture (COP) for a dispatch team, providing awareness of available information, information gaps, and the progress of emergency response operations. Together, cue filtering, the 6W domain ontology, and the function of CAD as a COP, enable analysts to create frames which, in turn, condition subsequent opportunities for distributed sensemaking activities of elaborating, questioning, and reframing.

Integrating Information from Social Media and 911 Callers: Elaborating the Emergency Frame

When a call is entered in CAD, the second phase of sensemaking proceeds as call takers and analysts seek to elaborate the existing frame by providing additional details about an emergency. As a frame, call information in CAD orients analysts' information seeking by articulating information requirements associated with gaps in "weapons," "who," "when," and "why" information prioritized according to the evolving needs of emergency responders. The simulations demonstrate how 911 calls entered in CAD provide analysts with resources for searching social media data and coordinating information seeking between call takers and analysts. However, the simulations also suggest analysts require assisted search features and information seeking protocols.

As a frame, a CAD call provides the dispatch team with a narrative of events happening during an emergency which analysts can, theoretically, use to search for priority information. In scenario one, for instance, the analyst knows that responders require immediate details about suspect(s) responsible for the mall shooting rather than survivors sheltering in place. However, while analysts use frames as stories to understand how information requirements associated with chronological events will likely evolve during an emergency, the simulations suggest analysts must also use frames as scripts to coordinate proactive information seeking among dispatch teams. Such protocols would direct analysts to search social media data for priority information addressing the information gaps dispatchers describe in CAD whenever entering new information. Moreover, such protocols would encourage analysts to proactively search for missing information rather than reactively search for information when prompted by 911 callers.

Proactive information seeking, however, requires the ability to search and discover priority information. During both scenarios, analysts' search heuristics proved ineffective when filtering large social media datasets. To select search terms, analysts adapted techniques developed as call takers and searched for place names (e.g. "Camp Road," "Belk") mentioned by 911 callers. These queries resulted in poor recall of relevant information. Consequently, social media analysis tools in emergency dispatch will likely require assisted search capabilities leveraging, for instance, keyword-based classifiers that would allow an analyst working with a single cue, such as the department store name "Belk," to filter social media data associated with all toponyms in that geographic location. Similar approaches could be leveraged for each of the 6Ws, allowing, for example, an analyst using the cue "shot people" to filter social media data using keywords and n-grams associated with potential victims, i.e. "who." Future efforts to implement assisted search features in social media analytics dashboards can draw on the extensive research surrounding automated classification techniques for crisis-related information (Imran, Castillo, Diaz, & Vieweg, 2015), but must tailor these techniques to the domain ontology organizing information processing in emergency dispatch work (Kropczynski et al., 2018).

Evaluating Inconsistent Information: Questioning and Reframing the Emergency

When dispatchers discover inconsistencies, they must evaluate if the discovered information is novel, supplementary, or redundant in relation to information characterizing the existing frame. If determined novel, call takers or analysts can reframe the emergency by entering a new call in CAD or replace an existing call. Reframing produces a new frame for the dispatch team that, in turn, re-starts the distributed sensemaking cycle. For analysts, the emergency frame comes into question when noticing inconsistencies between newly-discovered information on social media and call information in CAD characterizing the existing frame. Analysts notice inconsistencies when comparing among information discovered on social media (e.g. do tweets refer to different locations?) and between information from social media and information in CAD (e.g. do tweets refer to the same locations as 911 callers?).

During the simulations, however, analysts recognize inconsistencies rarely and, in the case of the "Pier One" example, often inadvertently. Instead, analysts face a common problem in sensemaking: we don't know what we don't know. Consequently, analysts will likely require automated alerts to discover information about potential emergencies not yet reported by 911 callers. In the mall shooting scenario, the alert notifying the analyst that the word "shooting" was tweeted provides an example. Important questions regarding effective keywords, frequency thresholds, and other measures for triggering alerts extend beyond the scope of this study. Furthermore, analysts will likely require information visualizations that not only highlight relevant cues in social media data but draw attention to inconsistencies among (e.g. comparing all available location cues) and between (e.g. comparing location cues against incident cues) 6W information discovered on social media, and between 6W information discovered on social media and call information in CAD. The analytics dashboard employed during the simulations visualizes social media data in typical ways: plotted on a map, if geocoded, or filtered by search criteria in a social media stream. Understanding the domain ontology of emergency dispatch work, and how dispatchers use cues to frame social media data, can inform domain-specific visualizations that may help analysts detect inconsistencies challenging existing frames.

CONCLUSION

Our study must be considered in light of limitations attending simulated emergency dispatch work. Despite involving professional dispatchers in the design of the simulations, including the construction of the social media datasets, real-world conditions will, of course, vary significantly. Issues such as the need to verify information reported on social media were not fully addressed in this study although they remain an import consideration in emergency responders' uses of social media (Hiltz & Plotnick, 2016; Reuter, Ludwig, Kaufhold, & Spielhofer, 2016). Consequently, the design requirements offered here require further investigation and empirical evaluation. For instance, the design of alerts, as Boersma et al. (2016) observed, remains a difficult balance between recall and precision: too many undermine the value and effectiveness of user notifications while too few risk missing critical information. Moreover, the utility of alerts will necessarily depend on the information behaviors of social media users in a geographic community and use cases for emergency dispatch and response. Furthermore, additional research is required to design and evaluate visualizations that can support sensemaking activities such as "questioning." While prior research can inform initial designs (Ntuen, Park, & Gwang-Myung, 2010; Stasko, Görg, & Liu, 2008), the domain-specific nature of information visualization will require iterative ideation and evaluation engaging dispatchers as domain experts and prospective end users.

Overall, the simulations conducted in this study suggest that social media analysts cannot adopt the reactive posture of call takers waiting on incoming 911 calls but must, instead, proactively seek and integrate missing information with information available from 911 callers. This proactive role will likely require effective filtering and automated alerts to notify the analyst of new and novel information, assisted search functions to increase the recall and precision of analysts' search queries, and information seeking protocols to address information gaps that evolve during an emergency response. Furthermore, analysts stand to benefit from custom visualizations that support top-down analysis by organizing and contrasting relevant information to assist sensemaking activities of framing, elaborating, questioning, and reframing.

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