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Contributions of Role-Playing Games: Advantages of Incorporating Social Media in Disaster Response

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Contributions of Role-Playing Games:
Advantages of Incorporating Social Media in Disaster Response

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Abstract

After a disaster, emergency managers need to know who needs help, what type of help they need, and how soon they need it. Traditionally, they have relied on 911 calls and ground assessments to collect this information. Because the needs of a population are not able to be identified in a timely manner by ground assessments and because individuals are often unable to get through to 911, many civilians in distress turn to social media outlets as a last-ditch effort to obtain the services they need. Due to the uncertainty concerning the accuracy of social media posts, responding to disaster related information sourced from social media is considered a liability by emergency managers. Historically, the academic literature has not focused on obtaining an in depth understanding of the post-disaster decision environment. As a result of this gap in the literature, academics have been unable to provide viable routing solutions for incorporating social media data in disaster response operations, emergency managers have refrained from using this data, and civilian's last-ditch efforts have been left unserved by officials. This research presents 2 spreadsheet-based role-playing games to combat these problems: *Logistics to the Rescue* and *Dispatch to the Rescue*. In both games, players assume the role of an emergency dispatcher, assigning locations to routes. *Logistics to the Rescue* is geared towards K-12 students and provides a platform to familiarize them with emergency response logistics. *Dispatch to the Rescue* is geared towards emergency management personnel and aims to communicate the benefits of incorporating social media data in disaster response while concurrently eliciting expert knowledge regarding the post-disaster decision environment. Individually, *Logistics to the Rescue* promotes students to pursue careers in STEM by providing a distinct narrative portraying engineering as creative and cooperative rather than technical and a-social, and *Dispatch to the Rescue* provides invaluable insights into the underpinnings of the environment emergency personnel work within after major

disasters. Both games serve as pedagogical tools for simulating post-disaster environments showcasing how engineering can be used to save more lives in a disaster response while reinforcing the benefits of incorporating social media in disaster response.

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1. Introduction

On October 29th of 2012, when Hurricane Sandy made landfall on the New Jersey coast, the US not only experienced one of the costliest natural disasters to date but it also experienced the first mass occurrence of civilian reliance on social media as a form of crisis communication (Council, 2012). Between October 27th and November 1st of 2012, Twitter recorded over 20 million tweets related to Sandy and on the day of its landfall FEMA's official Facebook page received an estimated 300,000 views (Cohen, 2013). Since then, many examples of civilians utilizing social media platforms to exchange real-time information in times of crisis have been recorded and various methods outlining how to harness this data have been documented. In 2014 digital volunteers at Micromappers harnessed information posted to social media platforms to compile a real-time map displaying areas heavily impacted by Typhoon Haiyan and their associated rescue requests (Mackenzie, 2013). In 2015 Google harnessed information posted to social media platforms, after the earthquakes in Nepal, to reunite families and inform loved ones of their safety through their website, Google Person Finder (Baker, 2016). In 2017 grassroots organizations were able to provide relief to over 14,600 victims of Hurricane Harvey by harnessing information posted to social media and compiling an interactive map consisting of pending/fulfilled rescue requests while concurrently mobilizing civilians with the necessary equipment to conduct these rescues (MacMillan, 2017) (Sullivan & Holley, 2017).

Traditionally, official response agencies have relied on ground assessments, that often take days to conduct, to collect vital information about civilian safety during disasters (James, 2016). The aforementioned civilian response efforts provide various examples of how official response agencies could harness social media data to more speedily cultivate this vital information. However, the emergency response community has been reluctant to incorporate social methods in their data collection efforts due to the negatively perceived credibility of the data retrieved from social platforms (Su et al., 2013). In 2012, NEMA surveyed a group of emergency response agency personnel and questioned them on their propensity to consider incorporating social media data in their disaster response operations. The survey reported that over 75% of respondents would not consider social media data unless they could be corroborated by a trusted source, a process which could take days to conduct (Su et al., 2013). In a disaster response, the rapid administration of supplies to affected areas significantly reduces human suffering and loss of life (International Federation of Red Cross and Red Crescent Societies, 2000). It is well known that the logistics of a disaster response operation critically influence its effectiveness and efficiency (Van Wassenhove, 2006). Consequently, it is critical to ascertain the advantages and disadvantages of employing social media data in response operations as the information concerning rescue requests significantly affects the delivery of relief to affected populations.

In the past, various studies, discussed in greater detail below, have evaluated the positive and negative consequences of integrating social media in disaster response for a variety of decision approaches (Kirac, Milburn, & Wardell, 2013) (Kirac & Milburn, 2015) (Milburn & Mullin, 2018). Due to lack of information, these analyses have focused on a narrow set of decision approaches founded on the academic ideologies of what an ideal disaster routing methodology should be rather than the emergency management principles that dictate what a realistic disaster routing methodology can be. In this paper, two games are presented with the objective of bridging the aforementioned information gap. *Logistics to the Rescue* aims to promote interest in the use of social media for disaster response in future generations by appealing to K-12 girls while *Dispatch to the Rescue* aims to both encourage the current emergency management community to use social media for disaster response and to elicit their expert knowledge on what constraints dictate how decisions are made in their community.

Logistics to the Rescue considers a single vehicle disaster response route planning problem. The game is targeted toward K-12 girls and consists of two rounds. The first-round mimics a 3-stage route planning process. Each stage corresponds to the revelation of new data; in stage 1 the students are present with only 911 calls, in stage 2 they are additionally presented with unverified social media posts, and in stage 3 the accuracy of the social media posts is revealed. In each subsequent step a subset of the route created in the previous step is captured. This gently introduces students to the permanence related to their routing decisions. The second-round mimics an online route planning environment where data evolves over time and where each decision made is locked in, no longer allowing for any route flexibility and exposing the harsh nature of disaster response.

Dispatch to the Rescue also considers a single vehicle disaster response route planning problem. This game consists of one round, with three steps, and is targeted toward members of the emergency management community. All three steps of the game mimic an online route planning problem and utilize data derived from a case study tailor-made to incorporate both 911 calls and social media posts. The first step of *Dispatch to the Rescue* covertly reveals unlabeled 911 calls to players. The second and third step reveal both 911 calls and social media posts but only the third step discloses their labels. Although all three steps are centered around the same routing problem and case study, the progressive disclosure of data in each step elicits distinct outcomes. Thus, each step has the potential to represent a distinctive routing strategy.

Section 2 provides a review of the related literature. Section 3 presents a detail overview of the design process. In Section 4, the instance development for both games is discussed. Sections 5 and 6 summarize the work and present the final conjectures.

2. Literature Review

In this section we review relevant routing literature and examine how the routing problems built-into the games relate to the existing literature on disaster relief routing. Additionally, we discuss the academic evidence substantiating the intentional decisions we made when designing *Logistics to the Rescue* to appeal to young female audiences as well as the intentional decisions made when designing *Dispatch to the Rescue* to elicit expert knowledge in the field of emergency response.

2.1 Disaster Routing

Previous publications have explored topics relating to the dispatch of emergency vehicles in disaster response. For example, Hsueh et al., (2008), Mguis et al., (2012), Wex et al., (2014), Kirac et al., (2013), Kirac and Milburn, (2015), and Mullin and Milburn, (2018), among others, allocate the position of demand locations on the schedules/routes of emergency vehicles by minimizing the total tour cost. Mguis et al., (2012) assesses the implementation of a dynamic vehicle routing problem with time windows when routing the transport of civilians, troops, freight, food, fuel, and prescription drugs in a post disaster operation. Wex et al., (2014) evaluates the performance of a parallel-machine scheduling problem for allocating rescue units. Kirac et al., (2013) analyzes how two decision approaches compare for a variety of disaster routing objectives and extends this work in Kirac and Milburn (2015) to compare the same approaches in a multi-objective disaster routing problem. Similar decision approaches are considered by Mullin and Milburn, (2018), whose work analyzes how various data properties and their implementations can maximize lives saved when employing a capacitated vehicle routing problem to plan and dispatch rescue teams. In each of the aforementioned papers, all demand must be served.

While there is ample literature related to the optimization of disaster routing, few works consider models whose objectives allow for unsatisfied demand to remain at the response stage.

Qin et al., (2017) notes that in the first 72 hours of a response, resources are constrained and consequently applies an emergency vehicle routing problem with insufficient supplies to route emergency vehicles. The objective is to minimize the total expected cost, and although each demand point is required to be visited by a vehicle, the total demand units at each point are not required to be satisfied at the end of the response stage. Subsequently, the shortage of a unit of supply at a demand point is penalized providing the model with incentive to serve as much demand as possible but allowing some demand to go unsatisfied. Najafi et al., (2014) proposes a mixed integer, multi-objective, multi-commodity, multi-modal model to dispatch and route vehicles in response to an earthquake. The model's objectives are hierarchical, primarily minimizing the number of unserved people and secondarily minimizing unsatisfied need. The number of unserved people and needs are penalized not only by their absolute amount but also by their associated severity as their weighted sums, by severity, are respectively added to objective functions 1 and 2. Kirac and Milburn, (2018) proposes the use of the team orienteering problem (TOP) to solve a mobile delivery problem in a disaster response environment. By definition the TOP maximizes lives saved, thus it does not require a penalty to account for unserved demand.

The goal of the games presented in this paper is to mimic the role of a dispatcher, working within the first 72 hours of a large-scale disaster response operation. A dispatcher's job is to relay uncertain information and organize the appointment of people/vehicles in emergency services. Due to its simplicity, this paper's formulation of this problem most closely resembles that presented by Kirac and Milburn, (2018), as players are asked to solve variants of the Orienteering Problem (OP), a special case of the TOP. For more information concerning the OP we direct readers to Tsiligirides, (1984) and Golden et al., (1987).

2.2 Disaster Routing Under Uncertainty: Future Needs

As previously mentioned, there are few works which allow for unsatisfied demand to remain at the end of a given time horizon, however, there are even fewer works who consider the uncertainty of data in a disaster response. Intuitively, the future needs of a disaster-stricken population are not known with certainty at the time of planning a disaster response. Most publications regarding disaster routing assume that all data are available in the planning stages of a disaster response (Najafi, Eshghi, & Sander, 2014). Two strategies have predominantly been used to model uncertainty in regard to future needs in disaster environments. Academics such as Najafi et al., (2014), Özdamar et al., (2004), Hsueh et al., (2008), and Mullin and Milburn, (2018) follow a dynamic planning strategy where data evolves over the response period and plans can be changed accordingly. Others such as Qin et al., (2017) and Shen and Dessouky, (2009) utilize a dynamic planning strategy where data evolves over the response period and a stochastic strategy where uncertain data is used to plan a response.

The games were developed to bridge an information gap between the academics modeling optimized rescue routes, the practitioners executing rescues, and the civilians being rescued. In disaster routing, the scheduling of demand within supply routes can drastically change depending on the objective of the model (Luis, Dolinskaya, & Smilowitz, 2012). This implies that any misinterpretation of the game, on the players behalf, will lead to insignificant results. Thus, given that stochastic modeling is considered to be an advanced topic in engineering and that the target audiences are comprised of emergency personnel and K-12 girls, both games consider variations of the dynamic programming strategy. Specifically, *Logistics to the Rescue*, considers a 3-step dynamic planning strategy where the player is allowed to re-route only after 2 specified time intervals. Additional demand information is only revealed at these specified times. In *Dispatch to* *the Rescue*, an online dynamic planning strategy is considered where the player is allowed to re-route only after they have arrived at a previously scheduled stop, at each stop new points may or may not be revealed.

2.3 Disaster Routing Under Uncertainty: Demand Accuracy

Less intuitive than the uncertainty of future demand, the accuracy of demand information is also unknown during the planning stage of a disaster response (Shen Z. & Dessouky, 2009). Despite having chosen to consider only 911 data, which they deem as high-quality data, the disaster response community continues to operate in conditions of extreme uncertainty (Tapia & Moore, 2014). A survey conducted by CNA and NEMA in 2012 found that more than 75% of the emergency management agencies surveyed stated that they would not consider social media data when creating disaster response plans unless the data could be verified by a credible source (Su, Wardell, & Thorkildsen, 2013). Interviews conducted with representatives from large international disaster response organizations by Tapia and Moore, (2014) corroborated these findings. In these interview summaries many subjects "stated that the veracity, accuracy, and legitimacy of data were the most important factors in data used in organizational decision-making" and the academics concluded that the subjects held "unreasonable standards for [social media] data, beyond the standards for the same data arising from more traditional sources [911]". Interestingly enough, these interviews also revealed that, in regard to 911 data, most subjects regretted that superior data was unavailable, accepted that this was the nature of their work, and understood that despite the shortcomings of the data, hundreds of lives had been saved.

From the aforementioned interviews, it is clear that despite being widely regarded as incomplete, 911 data is thought of with high esteem when compared to social media data. This can be explained by examining data that is recognized as being of high-quality. Data are defined as being of high-quality if their features are considered suitable for employment in a given field (Juran, 1988). Unofficial policies within the emergency management (EM) community dictate that only 911 demands are considered fit for consideration by response agencies, consequently boosting the perception of 911 data's quality, especially when compared to social media.

These unofficial policies have historically led academics to largely overlook the intrinsic uncertainty of data accuracy, as a whole, in disaster response. However, the concurrent rise of social media and billion-dollar disasters within the last decade has paved the way for a resurgence of academic interest in the uncertainty of data and its accuracy in high-risk decision environments. Kirac et al., (2013), Kirac and Milburn, (2015, 2018), Houston et al., (2015), and Mullin and Milburn, (2018) model disaster response problems under uncertainty and analyze the implications of incorporating uncertain social media data in disaster response. Athanasia and Stavros, (2015), Plotnick and Hiltz, (2016), and Tapia and Moore, (2014) examine and summarize the current and future roles of social media in disaster response by reviewing relevant literature and conducting expansive studies as well as interviews. All of the above-mentioned academics have indicated that social media has a lot of potential to become a useful tool in disaster response and that while the uncertain nature of this data does pose significant challenges, that the development of generalized models to quantify the improvements accomplished by incorporating this data might facilitate a shift in the perception of social media's role in disaster response. Moreover, the papers allude to the notion that the critical shift in EM agencies' perspectives is not likely to come from justifying that the qualities of social media data are comparable to those of 911 data. Instead, they propose that academics aid EM agencies in redefining their data performance metrics to measure helpfulness rather than accuracy.

The primary objective of both *Logistics to the Rescue* and *Dispatch to the Rescue* is to help expose the EM community as well as K-12 girls to the potential advantages of incorporating social data in disaster response. More specifically, both games are intended to reveal that disaster routes which consider both 911 and social data perform at least as good as, if not better than, disaster routes which only consider 911 data, even when accounting for highly inaccurate social media data. To accomplish this objective, experimental design choices were derived from Kirac et al., (2013), Kirac and Milburn (2015, 2018) and Mullin and Milburn, (2018) and integrated into a user-friendly format which could be easily distributed and accessible to EM personnel as well as K-12 girls. At the finally of both games, the routes created, by players, in each step are measured in terms of total lives saved and compared to one another. In *Logistics to the Rescue*, the routes are compared using a benchmark from a case study, with only 1 instance, where approximately 45% of the nodes revealed to the players are social media posts, and of those 60% are accurate. In *Dispatch to the Rescue*, the routes are compared using a case study, comprised of 22 instances. In each scenario approximately 30% of the nodes revealed to the players are social media posts. A total of 6 values denoting the proportion of social media posts considered accurate are used, 0%, 20%, 40%, 60%, 80%, and 100%. Each of these percentages, with the exception of 0% and 100%, has 5 replicates, each randomly distributing the accurate social media nodes within the pre-defined set social media nodes. The performance of the routes created in each step of this game are then compared for each instance in this case study, providing the player with a reliable portrait of how integrating social data in disaster can improve rescue outcomes in a variety of lifelike scenarios.

2.4 K-12 Education: Logistics to the Rescue

The design choices implemented throughout the development of *Logistics to the Rescue* focused on encouraging young women to pursue careers in STEM. This focus was driven by the disparate percentage of bachelor's degrees awarded to women compared to the percentage of engineering specific bachelor's degrees awarded to women. The National Science Foundation (NSF) has stated that in 2014 57% of bachelor degree recipients were women, while only 20% of engineering specific bachelor degrees were awarded to women (National Center for Science and Engineering Statistics, 2017). It has been shown that different engineering fields value different principles, which, consequently, affects the participation of women (Godfrey, 2007). Studies by the National Academy of Engineering have also shown that the use of empathetic and philanthropic language in job descriptions is effective in attracting more girls to engineering (National Academy of Engineering, 2008). Brawner et al. (2012) even documented that fields like industrial engineering allow women to "combine the prestigious social credentials of being an engineer with practices they value, without losing their sense of self". Consequently, we claim that *Logistics to the Rescue* can help bridge the aforementioned gender gap by emphasizing how industrial engineering can be utilized to aid disaster victims in times of crisis.

2.5 Eliciting Expert Knowledge: Dispatch to the Rescue

Dispatch to the Rescue's, contributions are twofold. Not only does the game stimulate interest in the incorporation of social media data within the EM community, as discussed in previous sections, but it also serves as a tool to elicit expert knowledge. The knowledge captured by *Dispatch to the Rescue* is beneficial for both the EM community itself and the academics studying it. To the EM community, it provides an assessment of the strategies employed by experienced emergency response personnel and a breakdown of how they utilize their skills and knowledge to manage time sensitive information in un-predictable environments. To academics, it provides a documentation of the expert knowledge employed by the emergency response personnel who operate as decision-makers in complex disaster scenarios.

There is extensive literature on eliciting expert knowledge. Schiuma et al., (2012) provides a thorough review of various knowledge elicitation methods and classifies them into one of three categories, analyst-leading, expert-leading, or expert-analyst collaborating. The analyst-leading and expert-leading methods require the active position to be held by analyst and experts, respectively. More specifically, methods such as interviews and questionnaires are classified as analyst-leading methods while round table discussions, brainstorming sessions, observational studies, and lectures are classified as expert-leading methods. Although experts and analysts assume active positions in both role-playing games and verbal reports, these methods are not classified as either analyst-leading or expert-leading. These methods require both analyst and experts to concurrently assume active positions and are classified as expert-analyst collaborating methods as defined in Schiuma et al., (2012).

Specialized techniques are used a priori, in analyst-leading methods, to craft questions intended to elicit expert knowledge (Schiuma, Gavrilova, & Andreeva, 2012). Therefore, it can be deduced that a thorough understanding of the decision process in question is a perquisite to applying these methodologies, an ideology supported by Schiuma et al., (2012) . In regard to dispatchers, the decision process they employ in post-disaster rescue operations varies not only by state but by county and even by dispatch center. In light of this, the application of an analyst-leading method to elicit expert knowledge in this field is implausible.

The role of an analyst is very limited in expert-leading methods. In fact, analyst engagement in these methods is typically restricted to communicating the topic and objectives of the activity and is sometimes extended to allow for questions regarding clarification on any statements or behaviors recorded by the analyst (Schiuma, Gavrilova, & Andreeva, 2012). In our experience, expert-leading methods can be very time consuming. Minimizing the time spent eliciting the expert knowledge of EM personnel such as dispatchers is of utmost importance as EM personnel operate in high-stakes environments where every second matters, making their time very costly (Moore & Miles, 1991). Consequently, precluding the use of expert-leading methods for eliciting expert knowledge within the EM community.

In the past, expert-analyst collaborating methods have been applied by academics to elicit expert knowledge within the EM community (Klein, Calderwood, & Macgregor, 1989) (Okechukwu Okoli, Weller, & Watt, 2014). Both Klein et al., (1989) and Okechukwu Okoli et al., (2014) employ a type of verbal report methodology, termed the critical decision method (CDM). The paper published by Klein et al., (1989) introduces the CDM method and provides an example of its application by employing it to investigate the decision differences between expert and novice firefighters. Okechukwu Okoli et al., (2014) expands this case study by utilizing the CDM to identify the training needs in the firefighting community. This paper pinpoints the tacit knowledge and skills used by expert firefighters and explores the implications of transferring this knowledge to novice firefighters. These publications validate the employment of expert-analyst collaborating methods to elicit expert knowledge within the EM community.

Although, the case study performed by Klein et al., (1989), validates the use expert-analyst collaborating methods in the form of verbal reports, i.e. the CDM, for eliciting expert knowledge in the field of EM and although his findings are corroborated by Okechukwu Okoli et al., (2014), the application of a more advanced expert-analyst collaborating method, a role-playing game, may be more appropriate in this domain. As previously mentioned, minimizing the time spent eliciting expert knowledge is of utmost importance in this domain. However, Klein et al., (1989) and Okechukwu Okoli et al., (2014) both reported that their interviews were roughly 2 hours long. Additionally, it has been reported that individuals are not consistently able to verbalize their decision process and that even when they are their explanation is only weakly correlated with their tacit knowledge (Schiuma, Gavrilova, & Andreeva, 2012). These findings not only indicate major temporal drawbacks to the use of verbal reports, i.e. the CDM, for eliciting expert knowledge in the field of EM but furthermore substantiate that the method itself may not be appropriate as its underpinnings may be perceived as very challenging and difficult by the experts in question.

In contrast to verbal reporting methods, role-playing methods engage experts and reveal their tacit and implicit decision-making processes (Schiuma, Gavrilova, & Andreeva, 2012). Instead of relying on the complex verbalization of an expert's decision process, games allow experts to be immersed in a simplified metaphor of reality. This facet of role-playing games allows for the direct expression of various decisions in what appears to the expert as a simplified yet legitimate environment (Barreteau, Page, & Perez., 2007). Moreover, Barreteau et al., (2007) states that games offer a new dimension of knowledge elicitation through the "observation of body language, attitudes, and direct actions during the game". In Barreteau et al., (2007) gaming sessions are categorized as either continuous or deterministic in terms of player freedoms. In games expressing continuous player freedom, experts create their own rules at given stages of the game and in those expressing deterministic player freedom, experts must follow the scenarios implemented by analysts. Deterministic player freedom allows analysts to elicit specified behaviors while continuous player freedom allows analyst to validate hypothesis about expert behaviors. Combined with the drawbacks of verbal reporting methods and the advantages presented by gaming methods *Dispatch to the Rescue* employs a role-playing game method incorporating both deterministic and continuous player freedoms.

3. Methodology

Ultimately, the goal of this research is two-fold, to understand the decision processes employed in post-disaster situations and to promote the use of social media data in such environments. Two games are presented to achieve this goal, *Logistics to the Rescue* and *Dispatch the Rescue*. While the incentives influencing the design of *Logistics to the Rescue* and *Dispatch the Rescue* differ, they both employ a variation of the orienteering problem (OP).

3.1 Orienteering Problem

The OP is an NP hard single-vehicle routing problem that deals with the selection of nodes to visit and the sequence of those visits. The problem itself aims to maximize the total profit collected from the selected nodes within a pre-determined time limit. In the OP, it may not be possible to visit all nodes within the time limit, simulating the realities of a disaster response operation where demand outweighs supply.

The fundamental OP variant utilized in this paper can be defined as follows. Consider a set of demand locations, $N = \{1, \dots, |N|\}$, where each demand location $i \in N$ is associated with a non-negative integer valued number of lives, S_i. At the time of planning, $t = 0$, N can be partitioned into two subsets: verified demand locations, N_v, whose rescue requests were sourced using traditional methods, and unverified demand locations, N_u, whose rescue requests were sourced through social media platforms. At $t = 0$, it is known that for each $n_{v_i} \in N_v$, its' associated number of lives is equal to exactly one, $S_i = 1$, and that for each $n_{u_i} \in N_u$, its' associated number of lives is equal to at most one, $S_i \in \{0,1\}$. The vehicle's route is assumed to begin and end at the station. The goal of this formulation is to determine a route, constrained by a time limit, $Tmax$, that visits a subset of N and maximizes the total lives saved.

3.2 Logistics to the Rescue

As previously mentioned, *Logistics to the Rescue* is intended to promote K-12 interest in the use of social media for disaster response. The game simulates a post-disaster environment where players assume the role of an emergency dispatcher, dynamically assigning demand locations to rescue routes. To mimic this decision environment, *Logistics to the Rescue* employs two dynamic variants of the OP described above, one in each of its rounds.

The game's first round mimics a 3-stage OP where $Tmax_1 = 74$. In this round, players are interrupted twice and introduced to previously unknown information at times $I = \{20, 50\}$. Throughout each stage of this round, players are able to experiment with their route plans prior to finalizing their decisions. In stage 1, only verified demand locations, N_v, are considered and players define a route, R_1, between time $0 \le t \le Tmax_1$ such that $R_1 \subset N_v$. Each $r_i^1 \in R_1$ is associated with a non-negative, arrival time a_i^1. In stage 2, the route created in stage 1 is interrupted at time $I_1 = 20$, and unverified demand locations, N_u, are revealed. In this stage, players define a route, R_2, between time $I_1 < t \le Tmax_1$. The demand locations visited between time $0 \le t \le I_1$ in R_2 are identical to those defined in this time period by R_1. Mathematically, this implies that $\forall r_i^2 \in R_2$ whose $a_i^2 \le I_1, r_i^2 = r_i^1 \in R_1$. Furthermore, $\forall r_i^2 \in R_2$ whose $a_i^2 > I_1, r_i^2 \in \{N_u \cup N_v\}$. In stage 3, the route created in stage 2 is interrupted at time $I_2 = 50$, and the accuracy of each of the previously disclosed unverified demand locations are revealed. By revealing the accuracy of these demand locations, N_u can be partitioned into two subsets, accurate unverified demand locations, N_{Au}, and inaccurate unverified demand locations, N_{Iu}. In this stage, players define a route, R_3, between time $I_2 < t \le Tmax_1$. The demand locations visited between time $0 \le t \le I_2$ in R_3 are identical to those defined in this time period by R_2. Thus, $\forall r_i^3 \in R_3$ whose $a_i^3 \le I_2, r_i^3 = r_i^2 \in R_2$ and $\forall r_i^3 \in R_3$ whose $a_i^3 > I_2, r_i^3 \in \{N_{Au} \cup N_v\}$.

The second round of *Logistics to the Rescue* mimics a 3-stage OP with real time execution. The OP formulation in this round is very similar to the formulation utilized in round 1, with a couple of key exceptions. In round 2, only one route is created, R. Once a demand location has been added to the route it is made permanent, eliminating the planning aspect allowed in round 1. In this round, previously unknown information is also revealed at times $I = \{20, 50\}$. Between times $0 \leq t \leq I_1$, players are only presented with verified demand locations, between $I_1 < t \leq I_2$ unverified demand locations are revealed, and between $I_2 < t \leq Tmax_1$ the accuracy of the unverified demand locations is disclosed. Consequently, it can be observed that $\forall r_i \in R$ whose $a_i \leq I_1$, $r_i \in N_v$, and that $\forall r_i \in R$ whose $I_1 < a_i \leq I_2$, $r_i \in \{N_v \cup N_u\}$, and lastly that $\forall r_i \in R$ whose $I_2 < a_i \leq Tmax_1$, $r_i \in \{N_v \cup N_{Au}\}$.

When creating routes in *Logistics to the Rescue*, by and large players define how demand locations are assigned. The assignment strategies employed in this game can be categorized as either *TRAD* strategies, those who only consider 911 calls, or *PLAY* strategies, those who consider some form of both 911 calls and social media posts. In *Logistics to the Rescue* only stage 1 of round 1 enforces a specific strategy, *TRAD*, by revealing verified demand locations and withholding unverified demand locations. Stages 2 and 3 of round 1, as well as round 2, allow players the flexibility to either employ a *TRAD* or *PLAY* strategy.

3.3 Dispatch to the Rescue

Dispatch to the Rescue is intended to encourage the emergency management community to use social media for disaster response and to elicit their expert knowledge on what constraints dictate how decisions are made in post-disaster environments. In parallel to *Logistics to the Rescue, Dispatch to the Rescue* simulates a post-disaster environment where players assume the role of an emergency dispatcher, dynamically assigning demand locations to rescue routes. To mimic this decision environment, *Dispatch to the Rescue* employs an online variant of the OP described in Section 3.1. In addition to the sets and parameters defined for the aforementioned OP variant, each demand location $i \in N$, in *Dispatch to the Rescue,* is associated with a non-negative opening time O_i. In each of its' 3 steps, a route, R, constrained by $Tmax_2 = 99$, is defined. Each $r_i \in R$ is associated with a non-negative, arrival time a_i. In *Dispatch to the Rescue* verified and unverified demand locations, N_v and N_u, are uniformly revealed in a dynamic fashion between time $0 \leq t \leq Tmax_2$. Unlike in *Logistics to the Rescue,* the accuracy of unverified demand locations is not disclosed to players at any point in time. Subsequently, the route created in each step must satisfy the following: $\forall r_i \in R,\ O_i \leq a_i \leq Tmax_2$ and $r_i \in \{N_v \cup N_u\}$. In steps 1 and 2 of *Dispatch to the Rescue* demand locations revealed to players are not labeled as either verified or unverified, instead all demand locations are labeled as "missions". In step 3, revealed demand locations are labeled as either "social media posts" or "911 calls", allowing players to distinguish verified demand locations from unverified demand locations. Unbeknownst to them, players are presented with both verified and unverified demand locations in step 2 while in step 1 they are only presented with verified demand locations. Consequently, the route created in step 1 further satisfies: $\forall r_i \in R,\ O_i \leq a_i \leq Tmax_2$ and $r_i \in \{N_v\}$.

Unlike *Logistics to the Rescue*, *Dispatch to the Rescue* offers players little flexibility in defining how demand locations are assigned based on their verified status. While players have the ability to dictate the assignment of a demand location based on its proximity and opening time in steps 1, 2, and 3 of the game, they can only weigh the cost of assigning an unverified demand location as opposed to a verified demand location in step 3. The assignment strategies employed in *Dispatch to the Rescue* can be categorized as either *TRAD, PLAY*, or *ALL* strategies. Strategies categorized as *TRAD* or *PLAY* remain as previously defined in Section 3.2 and strategies categorized as *ALL* are those who unbiasedly consider 911 calls and social media posts. By only revealing verified demand locations, step 1 enforces the *TRAD* strategy and, by not labeling demand locations as either verified or unverified, step 2 enforces the *ALL* strategy. In step 3 players are given the freedom to employ either a *TRAD, PLAY*, or *ALL* strategy.

4. Case Study

Two classes of information are available when solving the dynamic orienteering problem utilized in *Logistics to the Rescue* and *Dispatch to the Rescue*: (i) unverified demand locations whose requests were sourced from social media platforms and (ii) verified demand locations whose requests were sourced from traditional sources, such as 911. As previously mentioned, the accuracy of the requests made at unverified demand locations cannot be determined with full certainty until they can be corroborated by a trusted source. The development of the case studies used in *Logistics to the Rescue* and *Dispatch to the Rescue* are, respectively, discussed in sections 4.1 and 4.2.

4.1 Logistics to the Rescue

The case study utilized in *Logistics to the Rescue* is modified from an instance used in a previous version of the game. It is comprised of 23 nodes, representing 22 demand locations, $N_D = \{1,2, \dots ,22\}$ and a depot, $N_0 = \{0\}$. All nodes are imposed on a 20 X 20 grid with integer-valued coordinates. The depot is placed at (10,10), a centralized location. It is assumed that all nodes have a service time, ST, equal to 0.

A parameter $\rho = 0.45$ denotes the proportion $\frac{N_u}{N_D}$ and a parameter $\lambda = 0.6$ denotes the proportion $\frac{N_{Au}}{N_u}$. N_v is defined as $N_v = N_D \cap \overline{N_u}$ and N_{Iu} is defined as $N_{Iu} = N_u \cap \overline{N_{Au}}$. Each $i \in N_D$ represents a rescue request and is associated with an S_i and an opening time, $0 \leq O_i \leq I_1$. Moreover, each $i \in N_u$ is associated with an integer-valued accuracy reveal time, $A_i = I_2$, at which the accuracy of the requests made by unverified demand locations is revealed to players. The planning horizon of the case study spans from $t = 0$ to $t = Tmax_1$. For every $i \in N_v$, $S_i = 1$ and $O_i = 0$, for every $i \in N_{Au}$, $S_i = 1$ and $O_i = I_1$, and for every $i \in N_{Iu}$, $S_i = 0$ and $O_i = I_1$.

Table 1 provides a detailed overview of the case study data utilized in *Logistics to the Rescue*. The row associated with the depot, $Num = 0$, is highlighted in yellow to distinguish it from demand locations. Furthermore, the parameter S_i can be calculated from the listed data as $S_i = N_v + N_{Au}$, where N_v and N_{Au} are equal to the column vector under their respective labels.

Table 1: Logistics to the Rescue Case Study Data

Logistics to the Rescue Case Study Data							
Num	X	Y	O	ST	A	N_V	N_{Au}
0	10	10	0	0	-	-	-
1	4	19	0	0	0	1	0
2	15	15	0	0	0	1	0
4	10	2	0	0	0	1	0
6	9	19	0	0	0	1	0
7	8	9	0	0	0	1	0
9	19	5	0	0	0	1	0
10	18	9	0	0	0	1	0
12	20	18	0	0	0	1	0
13	19	16	0	0	0	1	0
18	7	20	0	0	0	1	0
20	5	13	0	0	0	1	0
21	2	2	0	0	0	1	0
19	2	9	20	0	50	0	1
3	17	17	20	0	50	0	1
11	1	10	20	0	50	0	1
14	8	3	20	0	50	0	1
16	17	3	20	0	50	0	1
17	14	2	20	0	50	0	1
5	7	6	20	0	50	0	0
8	11	7	20	0	50	0	0
15	8	12	20	0	50	0	0
22	2	12	20	0	50	0	0

4.2 Developing Benchmark Instances: Dispatch to the Rescue

The case study presented is comprised of 22 stylized scenarios modified from an academic instance we developed. Section 4.2.1 provides an overview of the methods used to generate the underlying academic instance and Section 4.2.2 discusses the stylized modifications applied to the academic instance.

4.2.1 Academic Instance

The academic instance considers a set of 26 nodes, $N_D = \{1,2,\ldots,25\}$ and $N_0 = \{0\}$. Each $i \in N_D$ is associated with an $S_i = 1$, an $ST_i = 0$, and an $0 \le O_i < Tmax_2$. The planning horizon of the case study spans from $t = 0$ to $t = Tmax_2$ and is partitioned into five time intervals, $T_1 = \{t \in \mathbb{Z} |\ t = 0\}, T_2 = \{t \in \mathbb{Z} |\ 0 < t \le 25\}, T_3 = \{t \in \mathbb{Z} |\ 25 < t \le 50\}, T_4 = \{t \in \mathbb{Z} |\ 50 < t \le 75\}$ and $T_5 = \{t \in \mathbb{Z} |\ 75 < t \le Tmax_2\}$. An ordered set $OD = \{0.2, 0.3, 0.4, 0.1, 0\}$ denotes the percent of demand locations whose opening time falls, respectively, within time intervals T_1, T_2, T_3, T_4, and T_5.

All nodes are imposed on a 16 X 16 grid. The depot is placed at (8,8), a centralized location. Demand locations are placed by generating a random set of 25 integer coordinates, within the 16 X 16 grid, iteratively until there are no duplicates. For the academic instance, parameter is defined $\rho = 0.32$. The set of demand locations and their coordinates is partitioned by defining N_u as a random sample of N_D such that $|N_u| = \lceil |N_D|(\rho) \rceil$, and by defining $N_v = N_D \cup \overline{N_u}$. To ensure that all verified and unverified demand locations are distributed fairly across both time and space, N_u and N_v are first partitioned into 5 subsets as shown in equations (1)-(6). The size of the random samples calculated in equations (1)-(6) is rounded to the nearest even number to ensure that the sum of all their magnitudes equals the total number of nodes. Once N_u has been partitioned, for $m = \{1, 2, 3, 4, 5\}$, it can be seen that $\forall i \in N_u^{Tm}$, $O_i \in T_m$. The same is true for N_v and its subsets.

$$N_J^{T1} = RandomSample\left(N_J, size = \left|N_J\right| * OD(1)\right) \tag{1}$$

$$N_J^{T2} = RandomSample\left(N_J \backslash N_J^{T1}, size = \left|N_J\right| * OD(2)\right) \tag{2}$$

$$N_J^{T3} = RandomSample\left(N_J \backslash (N_J^{T1} \cup N_J^{T2}), size = |N_J| * OD(3)\right) \quad (3)$$

$$N_J^{T4} = RandomSample\left(N_J \backslash (N_J^{T1} \cup N_J^{T2} \cup N_J^{T3}), size = |N_J| * OD(4)\right) \quad (4)$$

$$N_J^{T5} = RandomSample\left(N_J \backslash (N_J^{T1} \cup N_J^{T2} \cup N_J^{T3} \cup N_J^{T4}), size = |N_J| * OD(5)\right) \quad (5)$$

$$\forall J \in \{u, v\} \quad (6)$$

4.2.2 Stylized Scenarios

In order to assess the performance of the *TRAD*, *PLAY*, and *ALL* strategies, various scenarios are adapted from the academic instance described above. Scenarios are generated by assigning various proportions of accuracy to the unverified demand locations in the academic instance. More specifically, in the stylized scenarios λ is assigned a value from the following range, $\{0, 0.2, 0.4, 0.6, 0.8, 1\}$. The set N_u is partitioned by defining N_{Au} as a random sample of $N_u$such that $|N_{Au}| = \lceil |N_u|(\lambda) \rceil$, and by defining $N_{Iu} = N_u \cup \overline{N_{Au}}$. Because the requests associated with the locations in N_{Iu} are inaccurate, $\forall i \in N_{Iu}$, $S_i = 0$. Following the same logic, because the requests associated with the locations in N_{Au} and N_v are accurate, $\forall i \in (N_{Au} \cup N_v)$, $S_i = 1$. To vary the location distribution of N_{Iu} and N_{Au} within N_u this procedure is repeated 5 times for each $\lambda \in \{0.2, 0.4, 0.6, 0.8\}$ value, producing a total of 22 stylized scenarios which are split into 6 λ-defined categories.

The academic instance and its 22 stylized scenarios are depicted in Table 2. The row associated with the depot, $Num = 0$, is highlighted in yellow to distinguish it from demand locations. Furthermore, the parameter S_i, can be calculated from the listed data as follows. For any given scenario $S_i = N_v + N_{Au}$, where N_v and N_{Au} are equal the column vector under their respective labels.

Table 2: Dispatch to the Rescue Case Study Data

Academic Instance						Stylized Scenarios																					
Num	X	Y	O	ST	N_V	N_{Au}																					
						λ=0	λ=0.2					λ=0.4					λ=0.6					λ=0.8					λ=1
0	8	8	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
1	7	15	30	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	12	1	24	0	0	0	0	1	0	0	0	1	1	0	0	1	1	1	0	0	1	1	1	0	0	1	1
3	0	0	68	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	5	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	2	14	20	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	1	1	25	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	3	7	29	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	5	16	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	6	9	0	0	0	0	1	0	0	0	0	1	0	0	1	0	1	1	0	1	1	1	1	0	1	1	1
10	9	11	0	0	0	0	1	0	0	1	1	0	0	1	0	1	1	0	1	1	1	1	0	1	1	1	1
11	7	5	39	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	11	11	7	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	3	14	21	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	1	1
14	14	0	64	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	12	14	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	11	16	28	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	7	12	44	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	1	0	0	0	1	1	1	0	1
18	9	4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	2	13	35	0	0	0	0	0	1	0	1	0	1	1	0	0	1	1	1	1	0	1	1	1	1	0	1
20	3	1	27	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	13	7	3	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	1	1	0	1	1	1	1	1
22	16	15	26	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	5	4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	11	4	47	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1	0	1	1	1	1	1	1	1	1
25	14	2	15	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

5. Results

5.1 K-12 Survey Results: Logistics to the Rescue

Logistics to the Rescue has been administered to two groups of 6th and 7th grade female engineering summer camp students, once in 2018 and again in 2019. Cumulatively, a total of 35 campers, aged between 11 and 12 years, have played *Logistics to the Rescue* and responded to the survey questions shown in Table 3. The survey results show that 100.00% of the campers were in agreement that both their understanding of disaster response as well as their understanding of how social data can be used to support disaster response had improved as a result of the activity. Additionally, 96.30% of campers were in agreement that their interest in disaster response improved as a result of the activity and 96.00% were in agreement that their interest in the use of social data to support disaster response improved as a result of the activity.

Table 3: Logistics to the Rescue Survey Questions

Survey Questions	
On a scale from strongly disagree - strongly agree (1-5), rate your agreement with the following.	
Q1	My understanding of disaster response improved as a result of this activity.
Q2	My interest in disaster response improved as a result of this activity.
Q3	My understanding of how social data can be used to support disaster response improved as a result of this activity.
Q4	My interest in the use of social data to support disaster response improved as a result of this activity.
Q5	The challenge presented by this activity was appropriate for my skill level.
Q6	The challenge presented by this activity was appropriate for the skill level of other students in my grade.
Q7	In order to effectively administer relief, emergency response agencies should monitor social media throughout the course of a disaster.
Q8	Social media is an effective way to communicate with officials when 911 is unreachable.

The survey responses suggest that the game provided an appropriate level of difficulty for the 35 campers who partook in the activity. When asked to rate their agreement on whether the challenge presented by the activity was appropriate for their skill level, on a scale from strongly disagree to strongly agree, 96.43% of campers reported that they strongly agreed or agreed while the remaining 3.57% of campers reported a neutral stance. In fact, for both Q5 and Q6 on the survey, the median level of agreement is 4, indicating that the campers agree with the statements.

Our testing demographics are not exhaustive; however, the results collected suggest that *Logistics to the Rescue* is well-suited for 6th to 7th graders between the ages of 11-12 years-old.

5.2 K-12 Routing Results: Logistics to the Rescue

Logistics to the Rescue is comprised of 4 steps. Verified, unresolved unverified, and resolved unverified demand locations are successively revealed to players in steps 1-3, respectively. Step 4 dynamically reveals all the information from steps 1-3. This includes revealing verified and unverified demand locations as well as revealing the resolutions to the unverified demand locations. The terms unresolved and resolved are used to, respectively, describe the set of unverified demand locations before and after they have been partitioned into accurate and inaccurate unverified locations. In the following, we report performance metrics, such as lives saved and distance traveled per accurate visit, for steps 1, 2, 3, and 4 of *Logistics to the Rescue*. By measuring average distance per accurate visit rather than average distance per visit, we are able to quantify the cost of visiting inaccurate demand locations within the route.

As previously mentioned, in step 1 the only routing strategy that players are able to employ is the *TRAD* strategy. A total of 68.57% of campers were able to save the maximum number of lives saved by participants, 12. Of the campers who were able to achieve the maximum number of lives saved, the minimum average distance traveled per accurate visit was 4.14 units. The participants averaged 11.14 lives saved and 6.41 average distance units per accurate visit. 68.57% surpassed the average lives saved and 71.43% of students surpassed the performance of the average distance units per accurate visit.

In step 2 players are able chose to employ either the *TRAD* or *PLAY* strategy. In this step, the maximum number of lives saved by participants was 17. By effectively employing the *PLAY* strategy only one camper was able to save 17 lives while traveling an average of 4.34 units of distance per accurate visit. Campers averaged 12.43 lives saved and 5.93 average distance units per accurate visit. There were no campers, who chose to employ the *TRAD* strategy, that were able to surpass these averages. Of the campers employing the *PLAY* strategy, 52.94% were able to surpass the average number of lives saved and 58.82% were able to surpass the average distance traveled per accurate visit.

The set of unverified demand locations is partitioned into accurate and inaccurate unverified demand locations in step 3, allowing players to employ either the *TRAD* or *PLAY* strategy. In this step, 8.57% of campers achieved the maximum number of lives saved, 16. Of the campers who were able to achieve the maximum number of lives saved, the minimum average distance traveled per accurate visit was 4.56 units. Participants averaged 12.97 lives saved and 5.67 average distance units per accurate visit. 61.76% of campers employing the *PLAY* strategy were able to surpass both of these averages. Only one camper chose to employ the *TRAD* strategy and, consequently, was not able to surpass either average.

By dynamically revealing verified and unverified demand locations as well as resolutions to the unverified demand locations, step 4 allows participants to employ either the *TRAD* or the *PLAY* strategy. 37.14% of campers were able to achieve the maximum number of lives saved, 15. Of these campers the minimum average distance traveled per accurate visit was 4.32 units. Campers averaged 12.40 lives saved and 5.93 distance units per accurate visit. No campers who chose to employ the *TRAD* strategy were able to surpass these averages. 56.25% of campers employing the *PLAY* strategy were able to surpass the average number of lives saved and 59.38% were able to surpass the performance of the average distance units per accurate visit.

5.3 Emergency Management Survey Results: Dispatch to the Rescue

In 2019 Dispatch to the Rescue was administered to various emergency response personnel. The activity ranged in duration between 20 to 60 minutes with an approximate average duration of 35 minutes. Nineteen individuals responded to the survey shown in Table 4. The survey was presented to participants in two sections. One section, distributed prior to the activity, was termed the pre-survey and the other section, distributed after the activity, was termed the post-survey. The pre-survey delivered questions 1-7 and the post survey delivered questions 1-9. Pre- and post-survey questions 1-7 were intentionally overlapped in order to detect any game-related variation in responses.

Table 4: Dispatch to the Rescue Survey Questions

Survey Questions	
Rank the following from most - least (1-5) influential when ordering calls on the dispatch queue.	
Q1	Position on the 911 Call Backlog
Q2	Number of Victims
Q3	Age of Victims
Q4	Location's Proximity to Officers
Q5	Severity of Victim's Condition
On a scale from strongly disagree - strongly agree (1-5), rate your agreement with the following.	
Q6	Emergency response agencies cannot effectively administer relief in response to a major disaster without monitoring needs posted to social media.
Q7	Social media is an effective way for impacted individuals to communicate their needs with officials when 911 is unreachable.
Q8	My understanding of how social data can be used to support disaster response improved as a result of this activity.
Q9	My interest in the use of social data to support disaster response improved as a result of this activity.

Questions 1 through 5 of the survey are hierarchical survey questions intended to provide insight into how emergency response personnel prioritize 911 calls in a major disaster response operation. In both the pre- and post-survey, more than half of respondents reported that the severity of a victim's condition, Q5, was the most influential characteristic and that the position on the 911 call backlog, Q1, was the least influential characteristic when determining a calls placement on the dispatch queue. These results are reflected in Figure 1, where the weighted average of Q1 exceeds all others and the weighted average of Q5 is surpassed by all others. Additionally, Figure 1 provides rudimentary evidence that there is little change in the responses reported by participants for each characteristic in the pre- and post-survey.

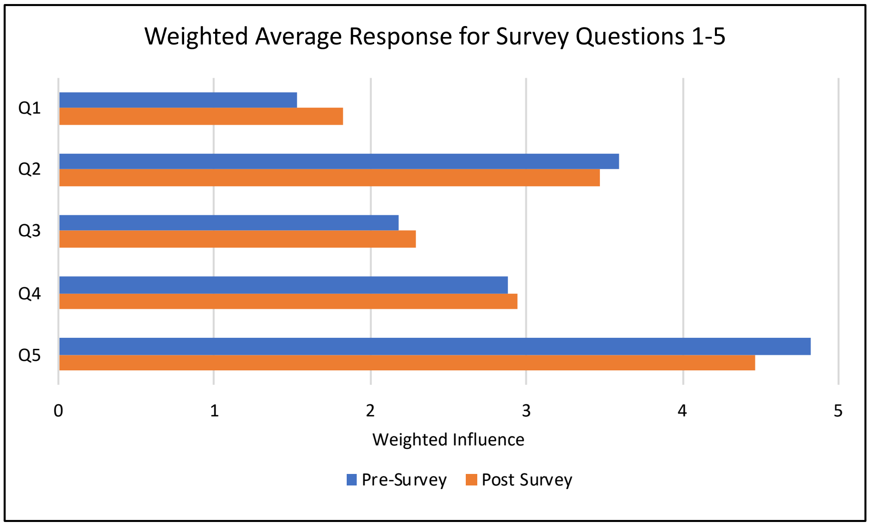

Figure 1: Pre- and post-survey weighted average response for questions 1-5. Weighted averages are proportional to influence.

A Friedman test was carried out to compare the influence ranking of the 5 call characteristics. There was found to be a significant difference between the characteristics, $\chi^2(4) = 81.66, p < 0.001$. Post hoc analysis with the Pratt-Wilcoxon signed-rank tests was conducted to further investigate the difference in influence for each characteristic from the pre-survey to the post-survey. For each question, 1-5, the results indicate that there is not enough evidence contained in this sample of data to reject the null hypothesis that the median difference is zero at a 0.05 level of significance. The p-values for each of these tests are shown in Table 5. Intuitively, the results make sense. Only 2 call characteristics on the list are considered by *Dispatch to the Rescue*, position on the 911 call backlog and locations proximity to officers. The objective of the game, to save maximal lives within a specified timeframe, favors prioritizing a location's proximity to officers over its position on the 911 call backlog and the pre-survey results show that even before playing *Dispatch to the Rescue*, participants ranked proximity over call order. These observations justify the test results.

*Table 5: Signed rank test results for survey questions 1-5, where * is significant at 0.05 and ** at 0.10.*

Pratt-Wilcoxon Signed Rank Test: Pre vs Post Survey Call Characteristic Influence				
			P-Values	
Question	W+	W-	Two-Sided	Directional ✝
Q1	53	32	0.56	0.281
Q2	33	66	0.688	0.344
Q3	51	48	1	0.5
Q4	91	71	1	0.5
Q5	31	68	0.46	0.203
✝Direction of the one sided test is determined by the sign of the largest W value, highlighted in blue.				

Questions 6-9 of the survey are Likert scale survey questions intended to collect information regarding particular statements of interest for this research. Figure 2 shows the agreement ratings for each of these questions. As reflected in Figure 2, responses for Q8 and Q9, were only collected in the post-survey. These responses show that 0% of respondents disagree with either Q8 or Q9 and that, respectively, 68.42% and 42.11% of respondents agree with Q8 and Q9. The median response for these questions is 4, signifying that the responses center around the “agree” category. Agreement ratings for Q6 and Q7 are collected twice, once in the pre-survey and again in the post-survey. In the pre-survey, 42.11% of respondents disagreed with Q6 while only 15.79% of respondents agreed. Furthermore, 21.05% of respondents disagreed with Q7 while 31.58% of respondents agreed. In the post-survey, agreement with Q6 and Q7, respectively, rose to 36.84% and 42.11% while disagreement, respectively, fell to 26.32% and 5.26%.

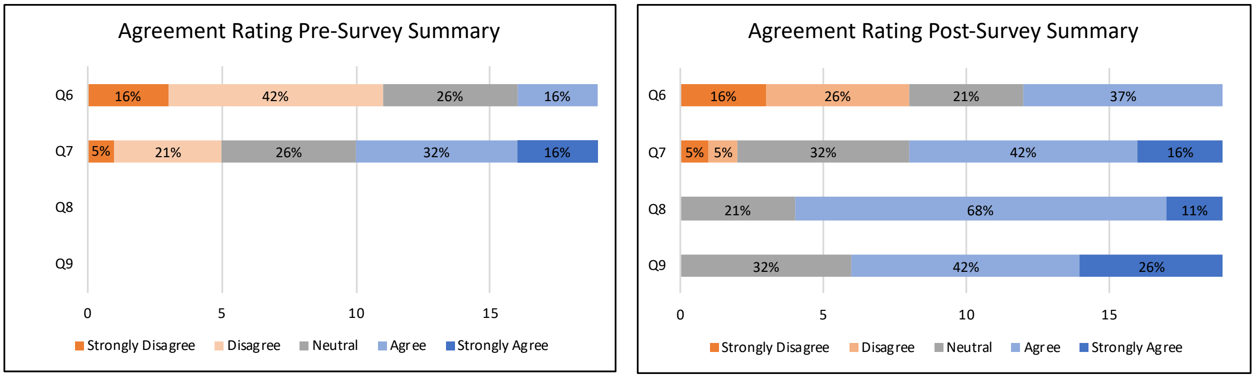

Figure 2: Pre- and post-survey agreement ratings. Percentages are rounded to the nearest whole number.

These results indicate that there is some change in the agreement reported by participants for these statements. The Pratt-Wilcoxon signed-rank test was performed on questions 6-7 to examine the difference in agreement from the pre-survey to the post-survey, the p-values are reported in Table 6. For Q6, at a 0.05 level of significance and with a sample of 19 pairs of differences, we reject H0 in favor of the alternative which states the difference in agreement between the pre-survey and the post survey is negative and that overall agreement with the statement increased. Similarly, for Q7, at a 0.10 level of significance and with a sample of 19 pairs of differences, we reject H0 in favor of the alternative which states the difference in agreement between the pre-survey and the post survey is negative and that overall agreement with the statement increased.

*Table 6: Signed rank test results for survey questions 6-7, where * is significant at 0.05 and ** at 0.10.*

Pratt-Wilcoxon Signed Rank Test: Pre vs Post Survey Likert Agreement Rating				
			P-Values	
Question	W+	W-	Two-Sided	Directional ✢
Q6	14.5	109.5	**0.055****	**0.027***
Q7	16	83	0.188	**0.094****
✢ Direction of the one sided test is determined by the sign of the largest W value, highlighted in blue.				

5.4 Emergency Management Routing Results: Dispatch to the Rescue

Dispatch to the Rescue is comprised of 3 steps. As previously mentioned, in step 1 only unlabeled verified data is revealed, in step 2 unlabeled verified and unverified data is revealed, and in step 3 labeled verified and unverified data is revealed. This enforces that in step 1 players employ the *TRAD* strategy, that in step 2 they employ the *ALL* strategy, and that in step 3 they employ their choice of either the *TRAD*, *PLAY*, or *ALL* strategy.

Routing results were collected from a total of 20 emergency response personnel. For each of these individuals, the routes they created in steps 1-3 were evaluated across six unique λ values for lives saved, distance traveled per accurate visit, and unverified points visited. Out of the 20 individuals, only 2 had routes whose averages across all six λ values saved more lives and traveled less distance units per accurate visit when employing the *TRAD* strategy, in step 1, instead of the *ALL* strategy, in step 2. Only 1 individual had routes whose averages saved more lives and traveled less distance units per accurate visit in step 1 than in step 3. Furthermore, only 1 individual had routes who on average included more unverified points in step 3 than in step 2.

Table 7 shows the average lives saved, average distance traveled per accurate visit, and average unverified visits in steps 1, 2, and 3 for each λ value. The final row of Table 7 reports the summary results over all participants and λ values.

Table 7: Routing averages for each λ. The final row, in blue, shows the averages of each individuals average across all λ's.

Routing Result Averages									
	Average Lives Saved			Average Distance per Accurate Visit			Average Unverified Visited		
λ	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3
0	14.85	13.60	14.25	6.48	7.19	6.84	0.00	6.95	5.70
0.2	14.85	15.42	15.80	6.48	6.33	6.16			
0.4	14.85	16.14	16.25	6.48	6.05	6.00			
0.6	14.85	17.92	17.75	6.48	5.44	5.50			
0.8	14.85	18.75	18.47	6.48	5.20	5.29			
1	14.85	20.50	19.90	6.48	4.76	4.92			
Avg λ	14.85	17.06	17.07	6.48	5.72	5.71			

From the summary row of Table 7 it can be observed that step 2, on average, saves more lives and travels less distance per accurate visit than step 1. Because step 2 enforces the application of the *ALL* strategy and step 1 enforces the application of the *TRAD* strategy, the results for these steps were used to conduct paired-samples t-tests. The first set of t-tests compared the lives saved in step 1 and step 2 and the second compared the average distance traveled per accurate visit in step 1 and step 2. The p-values for the first set of tests, shown in Table 8, indicate that for $\lambda = \{0.4, 0.6, 0.8, 1\}$, at a 0.05 level of significance and with a sample of 20 pairs of differences, we reject H0 in favor of the alternative which states the difference in lives saved between step 1 and step 2 is negative. This suggests that for $\lambda = \{0.4, 0.6, 0.8, 1\}$ the overall number of lives saved increased when employing the *ALL* strategy. For $\lambda = 0$, at a 0.05 level of significance and with a sample of 20 pairs of differences, we reject H0 in favor of the alternative which states the difference in lives saved between step 1 and step 2 is positive, suggesting that the overall number of lives saved decreased when employing the *ALL* strategy. Additionally, the p-values for the second set of tests, shown in Table 8, indicate that for $\lambda = \{0.4, 0.6, 0.8, 1\}$, at a 0.05 level of significance and with a sample of 20 pairs of differences, we reject H0 in favor of the alternative which states the difference in average distance traveled per accurate visit between step 1 and step 2 is positive. These results suggest that for $\lambda = \{0.4, 0.6, 0.8, 1\}$ the average distance traveled per accurate visit decreased when employing the *ALL* strategy. For $\lambda = 0$, at a 0.05 level of significance and with a sample of 20 pairs of differences, we reject H0 in favor of the alternative which states the difference in average distance traveled per accurate visit between step 1 and step 2 is negative, suggesting that the average distance traveled per accurate visit increased when employing the *ALL* strategy. The results from the first and second set of tests reveal that, for $\lambda =$

$\{0.4, 0.6, 0.8, 1\}$, employing the ALL strategy instead of the TRAD strategy allows players to more effectively utilize resources and save more lives.

*Table 8: Paired t-test for lives saved & distance traveled per accurate visit by the TRAD & ALL strategy, * is significant at 0.05.*

$D=L_1-L_2$	Paired T-Test: Lives Saved in Step 1 (L_1) vs Step 2 (L_2) by λ						
	Paired Differences					P-Values	
Pairs (D)	Mean (μ_D)	Std. Deviation	Std. Error	t	df	Two-Sided	Directional✢
λ=0	1.250	1.743	0.390	3.206	19	**0.005***	**0.002***
λ=0.2	-0.570	1.820	0.407	-1.401	19	0.177	**0.089****
λ=0.4	-1.290	1.759	0.393	-3.281	19	**0.004***	**0.002***
λ=0.6	-3.070	1.823	0.408	-7.531	19	**4.06E-07***	**2.03E-08***
λ=0.8	-3.900	1.902	0.425	-9.168	19	**2.09E-08***	**1.05E-08***
λ=1	-5.650	2.059	0.460	-12.272	19	**1.77E-10***	**8.87E-11***
Avg λ	-2.205	1.818	0.407	-5.424	19	**3.11E-05***	**1.56E-05***
$D=d_1-d_2$	Paired T-Test: Distance per Accurate Visit in Step 1 (d_1) vs Step 2 (d_2) by λ						
λ=0	-0.703	1.052	0.235	-2.989	19	**0.008***	**0.004***
λ=0.2	0.158	0.911	0.204	0.775	19	0.448	0.224
λ=0.4	0.436	0.835	0.187	2.338	19	**0.030***	**0.015***
λ=0.6	1.046	0.747	0.167	6.262	19	**5.17E-06***	**2.58E-06***
λ=0.8	1.285	0.728	0.163	7.898	19	**2.03E-07***	**1.01E-07***
λ=1	1.728	0.681	0.152	11.353	19	**6.57E-10***	**3.28E-10***
Avg λ	0.767	0.794	0.178	4.315	19	**3.73E-04***	**1.87E-04***

✢Direction of the one sided test is determined by the sign of the mean of the paired differences, μ_D.

Similarly, it can also be observed from the summary row in Table 7 that step 3, on average, saves more lives and travels less distance per accurate visit than step 1. However, because step 3 allows players to choose whether to employ the *ALL, TRAD,* or *PLAY* strategy, results from step 3 cannot be used to compare a specific strategy against the *TRAD* strategy documented by step 1. Instead of utilizing the results from steps 1 and 3 to compare specific strategies, the results were used to run two sets of t-tests to, respectively, compare the impact that revealing unverified demand locations/social media posts had on lives saved and distance traveled per accurate visit. The p-values for the first set of tests, shown in Table 9, indicate that for all $\lambda = \{0.2, 0.4, 0.6, 0.8, 1\}$, at a 0.05 level of significance and with a sample of 20 pairs of differences, we reject H0 in favor of the alternative which states the difference in lives saved between step 1 and step 3 is negative. This suggests that for $\lambda = \{0.2, 0.4, 0.6, 0.8, 1\}$ the overall number of lives saved increased when unverified demand locations/social media posts were revealed. For $\lambda = 0$, at a 0.05 level of significance and with a sample of 20 pairs of differences, we reject H0 in favor of the alternative which states the difference in lives saved between step 1 and step 3 is positive and that the overall number of lives saved decreased when unverified demand locations/social media posts were revealed. The p-values for the second set of tests, show that for all $\lambda = \{0.2, 0.4, 0.6, 0.8, 1\}$, at a 0.05 level of significance and with a sample of 20 pairs of differences, we reject H0 in favor of the alternative which states the difference in average distance traveled per accurate visit between step 1 and step 3 is positive, suggesting that for $\lambda = \{0.2, 0.4, 0.6, 0.8, 1\}$ the average distance traveled per accurate visit decreased when unverified demand locations/social media posts were revealed. For $\lambda = 0$, at a 0.05 level of significance and with a sample of 20 pairs of differences, we reject H0 in favor of the alternative which states the difference in average distance traveled per accurate visit between step 1 and step 3 is positive and that the average distance traveled per accurate visit increased when unverified demand locations/social media posts were revealed. The aforementioned results reveal that, for $\lambda = \{0.2, 0.4, 0.6, 0.8, 1\}$, choosing to reveal rather than conceal unverified demand locations/ social media posts allows players to more effectively utilize resources and save more lives.

*Table 9: Paired t-test comparing lives saved & distance traveled per accurate visit when considering only 911 calls & both 911 calls & social media posts, * is significant at 0.05.*

$D=L_1-L_3$	Paired T-Test: Lives Saved in Step 1 (L_1) vs Lives Saved in Step 3 (L_3) by λ						
Pairs (D)	Paired Differences: Mean (μ_D)	Paired Differences: Std. Deviation	Paired Differences: Std. Error	t	df	P-Values: Two-Sided	P-Values: Directional ✢
λ=0	0.600	1.353	0.303	1.983	19	**0.062***	**0.031***
λ=0.2	-0.950	1.301	0.291	-3.266	19	**0.004***	**0.002***
λ=0.4	-1.400	1.306	0.292	-4.795	19	**1.26E-04***	**6.30E-05***
λ=0.6	-2.900	1.365	0.305	-9.501	19	**1.19E-08***	**5.96E-09***
λ=0.8	-3.620	1.446	0.323	-11.192	19	**8.33E-10***	**4.16E-10***
λ=1	-5.050	1.761	0.394	-12.822	19	**8.40E-11***	**4.20E-11***
Avg λ	-2.220	1.330	0.297	-7.465	19	**4.63E-07***	**2.31E-07***
$D=d_1-d_3$	Paired T-Test: Distance per Accurate Visit in Step 1 (d_1) vs Step 3 (d_3) by λ						
λ=0	-0.353	0.540	0.121	-2.927	19	**0.009***	**0.004***
λ=0.2	0.320	0.485	0.108	2.949	19	**0.008***	**0.004***
λ=0.4	0.483	0.479	0.107	4.510	19	**2.40E-04***	**1.20E-04***
λ=0.6	0.987	0.471	0.105	9.361	19	**1.51E-08***	**7.54E-09***
λ=0.8	1.195	0.477	0.107	11.197	19	**8.27E-10***	**4.14E-10***
λ=1	1.565	0.510	0.114	13.712	19	**2.64E-11***	**1.32E-11***
Avg λ	0.770	0.472	0.106	7.294	19	**6.43E-07***	**3.22E-07***
✢Direction of the one sided test is determined by the sign of the mean of the paired differences, μ_D.							

Lastly, the average unverified visits documented in Table 7 show that step 2, on average, visits more unverified demand locations than step 3. Because step 2 considers the same set of points as step 3 but conceals their source by labeling both verified and unverified demand locations as "missions", the results collected from these steps were used to analyze the perception that the participants held of social media. The p-values, shown in Table 10, indicate that, at a 0.05 level of significance and with a sample of 20 pairs of differences, we reject H0 in favor of the alternative which states the number of visits to unverified demand locations between the step 2 and step 3 is positive. These results show that the number of visits to unverified demand locations decreased when their origin was disclosed, implying that emergency response personnel hold negative perception of the data collected through social media and are less inclined to incorporate it into their rescue routes.

*Table 10: Paired t-test comparing number of unverified/social media demand locations visited when demand location source was unknown and when it was known, * is significant at 0.05.*

Paired T-Test: Social Media Posts Visited in Step 2 (S_2) vs Social Media Posts Visited in Step 3 (S_3)							
Pairs: $D=S_2-S_3$	Paired Differences			t	df	P-Values	
	Mean (μ_D)	Std. Deviation	Std. Error			Two-Sided	Directional^{+}
Pair 1	1.25	1.293	0.289	4.324	19	**3.65E-04***	**1.83E-04***
$^{+}$Direction of the one sided test is determined by the sign of the mean of the paired differences, μ_D.							

6. Conclusion

Surveys distributed to the general public by The American Red Cross reveal that 80% of respondents expect emergency managers to monitor social sites, 20% of respondents would turn to an online channel if unable to reach 911, and over 30% expect responders to arrive within 60 minutes of posting a rescue request to a social media platform (The American Red Cross, 2011). In contrast, a survey distributed to emergency personnel by NEMA revealed that over 75% of respondents would not consider unverified social media data unless it could be corroborated by a trusted source (Su et al., 2013). The results documented by these surveys suggest that the general public's perception of current emergency procedures and the actual emergency procedures followed by emergency personnel do not align. As previously mentioned, current verification methods can take days to conduct, thus, any miscommunication concerning disaster procedures between the public and officials can have life threatening implications. The vital discrepancy between civilian expectation and official procedure motivated us to educate the public in regard to standard S.A.R procedures and to, within the emergency response community, promote the exploration of avenues in which standard S.A.R procedures may be improved upon. *Logistics to the Rescue* allows its students to contend with the trade-offs between incorporating unverified/social media demand locations, saving the maximal number of lives, and effectively utilizing limited resources. *Dispatch to the Rescue* provides emergency response personnel a liability free way of comparing the outcome of routes created with and without unverified/social media demand locations.

The contributions of the games presented in this thesis are three-fold. As shown in Figure 3, *Logistics to the Rescue* contributes to the K-12 literature by utilizing specialized tactics, such as highlighting the intersection of the social sciences and STEM as well as showcasing how engineering can help save more lives in a disaster, to encourage girls to pursue careers in STEM fields. Moreover, *Dispatch to the Rescue* contributes to the expert knowledge elicitation literature by expanding the repertoire of expert-analyst collaborating methods applied within the domain of disaster response by extending the application of role-playing games to the field. Lastly, both games contribute to the disaster routing literature by introducing models which more realistically simulate the actual decision environment experienced by emergency managers in post-disaster situation.

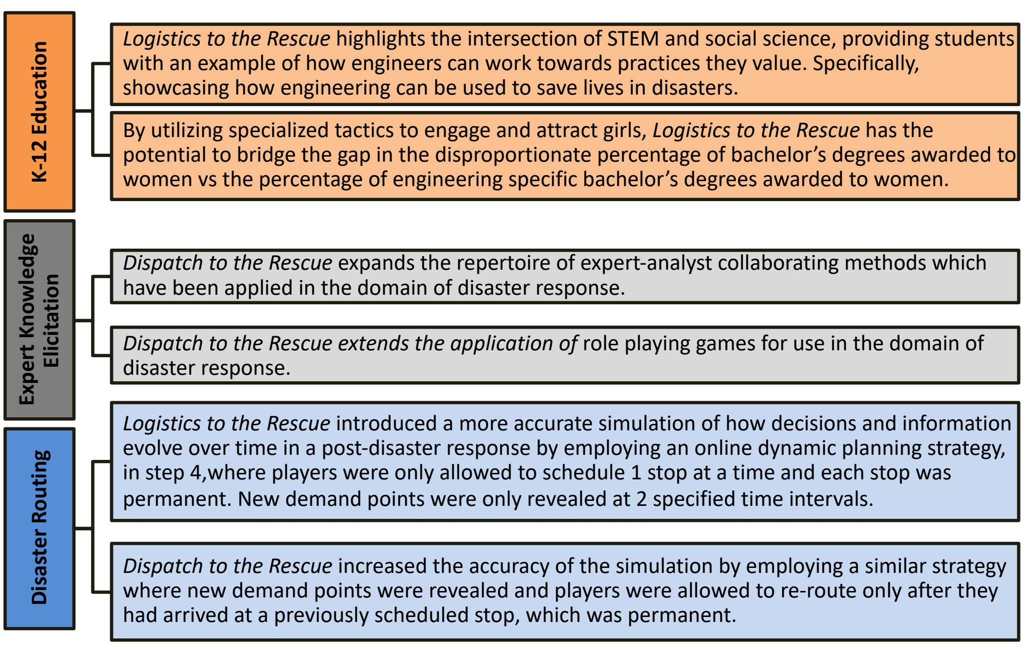

Figure 3: Contributions to the literature.

It is our opinion that *Dispatch to the Rescue* and *Logistics to the Rescue* can, respectively, encourage emergency response personnel to consider the exploration of alternative routing methods to improve disaster response operations and educate the next generation on the elementary concepts of S.A.R.

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8. Appendix

UNIVERSITY OF ARKANSAS

Office of Research Compliance
Institutional Review Board

March 29, 2018

MEMORANDUM

TO:	Ashlea Bennett Milburn Justin Taylor Erin Mullin
FROM:	Ro Windwalker IRB Coordinator
RE:	EXEMPT PROJECT CONTINUATION & MODIFICATION
IRB Protocol #:	15-12-439
Protocol Title:	*CAREER: Information Accuracy and the Use of Social Data in Planning for Disaster Response*
Review Type:	☒ EXEMPT
New Approval Date:	03/29/2018

Your request to extend and modify the referenced protocol has been approved by the IRB. We will no longer be requiring continuing reviews for exempt protocols.

If you wish to make any modifications in the approved protocol that may affect the level of risk to your participants, you must seek approval *prior to* implementing those changes. All modifications should be requested in writing (email is acceptable) and must provide sufficient detail to assess the impact of the change.

If you have questions or need any assistance from the IRB, please contact me at 109 MLKG Building, 5-2208, or irb@uark.edu.

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