

## **Using IoT Sensors to Enhance Simulation and Training in Multiteam Systems**

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### **ABSTRACT**

The vast amount of data being collected by sensors and wearable devices in healthcare simulations has yet to be harnessed to improve our understanding of teamwork and coordination between teams. For instance, a recent paper argued that several constructs serve as essential indicators of the quality of between-team activities including coordination, boundary spanning, and adaptation (Lazzara, Keebler, Shuffler, Patzer, Smith, & Misasi, 2015). This is a valuable theoretical insight, but the key to unlocking the full potential for real-world application in training and simulation is dependent on our ability to find proxies to measure those phenomena. Sensors that record proximity, position (GPS), and speech pattern data have been used as proxies for coordination, communication, and other team processes, including task management, situational awareness, and decision-making (Feese, Burscher, Jonas, & Tröster, 2014; Rosen, Dietz, Yang, Priebe, & Pronovost, 2014). Generally, data are gathered throughout an entire simulation, without a focus on which team inflection points and performance episodes are most important to capture. Moreover, emergency response scenarios are often handled by a complex system of teams varying in their between-team interdependencies. These systems are referred to as multiteam systems (MTSs), which are made up of two or more teams that work together interdependently toward a common goal, while separately working toward more proximal goals (Mathieu, Marks, & Zaccaro, 2001). In this paper, we review the data sources being used to describe team behaviors, discuss how to make decisions about data collected during MTS scenarios, and the importance of the data validation process. Two case studies (one Healthcare and one Fire and Rescue scenario) are reported to demonstrate the use of various sensors during simulations. Finally, directions for reporting data in after action reviews and the implications for training using an event-based approach are provided.

### **ABOUT THE AUTHORS**

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**Michael Au** is a recent graduate from George Mason University and holds a degree in Electrical Engineering. He has a passion in embedded systems and has programmed microcontrollers to perform hardware automation. For this project, he has written script to create graphical visualizations of collected sensor data.

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### INTRODUCTION

*“Hiding within those mounds of data is knowledge that could change the life of a patient, or change the world.” – Atul Butte, MD, Ph.D.*

Data analytics has already drastically changed the way consumers shop, the way companies understand their performance over time, the way financial advisors make investment decisions, and the way employees are screened and hired. Similarly, large data sets are being utilized in both hospital and emergency response settings, where decisions can result in life or death outcomes. For example, data have been used to track how many patients doctors see every hour and how often those patients come back for avoidable follow-up appointments (Olguin, Gloor, & Pentland, 2009). Additionally, Fire and Rescue forces have tracked the heart rates of their personnel to provide early warning for potentially dangerous health situations (Mordecai, 2008), because the greatest cause of firefighter fatalities is stress and overexertion (Fahy, LeBlanc, & Molis, 2016). Wearable devices and Internet of Things (IoT) sensors are also becoming increasingly common in tracking worker actions and responses during both simulations and live emergency response scenarios. However, much of the data being collected has yet to be harnessed for the improvement and understanding of *teamwork* and coordination both *within and between teams*.

While much of the data being collected are being acted on at the individual level (e.g., individual performance rewards, individual safety), some researchers have pointed out how proximity, position (GPS), and speech pattern data can be used as evidence of communication, task management, situational awareness, and decision-making at the team level (Feese, Burscher, Jonas, & Tröster, 2014; Rosen et al., 2014). These types of data can make a major contribution to the assessment of teams and the development of team training as a complementary information source when combined with current team-level data collected through self-report surveys and interviews.

In addition to the impact of real-time objective data on *team* assessment and training, there is an even bigger potential for impact in the context of *multiteam systems*. Multiteam systems (MTS) are tightly coupled groups of teams, often common in emergency response situations, in which the teams each carry out separate responsibilities while working toward a common goal (Mathieu, Marks, & Zaccaro, 2001), for instance, a hand-off for an injured patient brought by Emergency Medical Services team from a fire incident scene to the a Traumacare team. Oftentimes in healthcare, the handoff of information between teams is the most critical moment, and can be the most substantial threat to patient safety (Riesenberg, 2012). Therefore, *between-team training* is vital for MTSs. However, there is only one published manuscript that specifically discusses MTS training (see Firth et al., 2015). The development of technology-based training specifically for MTSs will help improve performance in some of the most critical and complex worker situations and address the distinctive issues these systems face. Effective MTSs are made up of strong component teams that are focused on their individual roles within the system, as well as the larger system goal.

We study two contextual examples of emergency response MTSs (i.e., Healthcare and Fire), and how their training and performance can be understood through behavioral data analytics. We first review the literature on technologies used to study team interactions, highlight their successes and challenges, and describe the implications of the data collected during two MTS simulations. We demonstrate that by defining key moments in a scenario (particularly those of between-team collaboration), a priori data analysis decisions can be made more effectively.

## THE MULTITEAM SYSTEM CONTEXT

In emergency response contexts where time is critical and situations are complex, involving many moving parts, multiteam systems are often formed. Each team works toward a proximal goal, generally specific to its discipline/specialty. At the same time, the teams within the system all work interdependently toward a common distal goal (Zaccaro, Marks, & DeChurch, 2012). For example, within the healthcare scenario, the emergency response team needs to arrive on scene expediently, stabilize the victim, and transport him or her to a hospital where additional care can be provided by the emergency department team, sometimes being handed off to a surgical team where trauma can be repaired. Any of the teams involved in this system are working towards a shared distal goal: patient recovery. Table 1 shows two different types of emergency response MTSs and lists each component teams and its role within the MTS, including both proximal and distal goals (See Figure 1 and Figure 3 for visual representations of the MTSs described in Table 1).

Table 1: Emergency Response Multiteam System Examples

| MTS             | Characteristics   | Component Teams                      | Component Team Proximal Goals  | Distal Goal   |
|-----------------|---|--------------------------------------|--|---|
| Healthcare      | <sup>1</sup> <b>Leadership:</b> Shared Distributed<br><sup>2</sup> <b>Interdependence:</b> Sequential<br><sup>3</sup> <b>Boundary Type:</b> External  | Pre-Hospital Emergency Response Team | Short on-scene arrival time, Short on-scene duration time, Stabilize patient for transport                         | Initiate patient treatment as quickly and effectively as possible       |
|                 |   | Emergency Department Team            | Holistic, prompt, appropriate patient management   |   |
| Fire and Rescue | <b>Leadership:</b> Vertical Multilevel<br><b>Interdependence:</b> Intensive<br><b>Boundary Type:</b> Internal or External ( <i>depending on whether fire and rescue are part from the same organization</i> ) | Fire Suppression (Engine; x2)        | Control and extinguish fire  | Quickly respond to and neutralize fire scene while rescuing any victims |
|                 |   | Ventilation (Tower; x2)              | Appropriately open access points to enable entry or removal of gases/smoke; search and rescue of potential victims |   |
|                 |   | Battalion Chief                      | Lead and direct all fire department members on scene   |   |
|                 |   | Basic Life Support/EMT               | Provide initial aid to victims and transport those needing more serious care                                       |   |

MTSs are significantly more complex than large teams. Various scholars have explained that simply using traditional team theory to understand multiteam systems is insufficient to describe phenomena that emerge at the system level (Davison et al., 2012; Firth, Hollenbeck, Miles, Ilgen, & Barnes, 2015; Lanaj, Hollenbeck, Ilgen, Barnes, & Harmon, 2013). For example, team coordination (i.e., the timing and sequencing of interactions among team members) manifests differently at the team and MTS levels. The timing and sequencing of interactions *between-teams* experience issues such as handoff quality (DeChurch, 2013). When component teams within a system have separate norms, work processes, and goals (Luciano et al., 2015), coordination becomes complicated at the MTS level, and can be challenging to execute. Firth and colleagues (2015) warn that MTSs with strong within-team coordination may still fail if their between-team coordination is weak. Thus, the type of training and after action reviews targeted at MTSs must consider both levels of interaction.

Another differentiating factor of MTSs that can cause potential challenges to success is the fact that the teams within the MTS are not always from the same organization. When component teams are from separate organizations, they

<sup>1</sup> *Distributed* leadership exists when multiple individuals share leadership responsibilities. *Multilevel* leadership is hierarchical with a clear leader of the entire team or MTS (Zaccaro & DeChurch, 2012).

<sup>2</sup> *Sequential* interdependence exists when one team hands off work to another team, often with some coordination during handoff. *Intensive* interdependence occurs when teams work extremely closely together and complete very little work in isolation. (Zaccaro et al., 2012).

<sup>3</sup> *Internal* MTSs are made up of teams from a single organization. *External* MTSs have teams from multiple organizations. (Zaccaro et al., 2012).

are referred to as *external* (as opposed to *internal*) MTSs (Zaccaro et al., 2012). For example, some cities have Fire and Rescue teams, while other cities have two separate organizations: one for fire and one for rescue. External MTSs are often at a higher risk of having different protocols, norms, and training practices. When used correctly, technologies and sensors can be used both as a diagnostic tool of MTS interaction and as a measurement of success.

Additionally, there is a distinct difference between team leadership and MTS leadership. For example, each truck and each engine in a fire MTS has its own leader, but the Battalion Chief operates as the MTS leader. This is a vertical, multilevel expression of leadership (see Table 1), such that the component team leaders report directly to the MTS leader. In other contexts, leadership is distributed, and different individuals are responsible for different leadership activities (Zaccaro & DeChurch, 2012).

The extent to which differences between component teams, whether the MTS is internal and external, and the leadership style matters depends on how interdependent component teams are. If interdependence is additive (i.e., success is a pure sum of component team efforts), then the group is not an MTS because, by definition, each component team in an MTS must work closely with at least one other team in the system (Zaccaro et al., 2012). MTS interdependence can range from *sequential* (handoff of information or resources from one team to another) to *intensive* where the teams work closely together throughout almost the entire process (Tesluk, Mathieu, Zaccaro, & Marks, 1997).

## REVIEW OF DATA SOURCES

Training is inherently coupled with performance, and team performance evaluation is comprised of standardized diagnostic tools to measure behaviors, cognitions, and attitudes of team members regarding operationalized criteria. In this way, evaluation should not only allow for information capture on *what* outcomes are obtained, but also *how* these outcomes are obtained (Rosen, Weaver, Lazzara, Salas, Wu, Silvestri, Schiebel, Almeida, & King, 2010). To facilitate this information capture, and ultimately inform training, various data streams including IoT sensors and other technologies have been developed.

Observation-based methods are a primary means of capturing team performance (Rosen et al., 2014). Video data provide a rich context in which to observe team behaviors. Coding footage for behavior analysis has leaned heavily on activity theory, which holds activity as the unit of analysis (Fjeld, 2002). An activity consists of a subject, an object, and a mediating tool. *Activity theory* acknowledges that individuals are not static, but shift dynamically in response to changing conditions (Leont'ev, 1974). Thus, using activity theory as a basis for data analysis provides a greater understanding of the knowledge involved, and the social and technological context involved in various performance episodes (Kofod-Peterson & Cassens, 2006). Within the healthcare context, behavioral analysis of video data can include such components as verbal communication, nonverbal communication, contact with patient, and presence on scene. Video footage can capture details that a human observer would miss and can be replayed with fidelity, however coding this footage is laborious and observation may not scale well when wishing to study large groups of actors.

Unobtrusive, wearable sensors have allowed for the collection of real-time data regarding proximity, positioning, and speech patterns (Feese et al, 2014; Rosen et al. 2010). Using smartphone sensor data, (Feese, Arnrich, Troster, Burtscher, Meyer, & Jonas, 2013) monitored firefighters in-situ during a real-world mission for the purposes of informing after action reviews and future training. Team effort was measured as the amount, intensity and variability of physical activity, with the justification that higher team effort can be expressed in more physical activity. Team coordination was captured as the amount of speech activity, with the reasoning that the more explicitly the firefighters will need to coordinate their actions, the more communication will be necessary. Additionally, radiofrequency identification (RFID) tracking and barcode registration for automatic instrument detection have both been used as proxies for situational awareness (Kranzfelder, Schneider, Gillen, & Feussner, 2011).

Using smartphone data, Feese and colleagues (2014) used analogous sensor information and social network analysis to visualize how long team members were together in a sub-group and how synchronized these members moved allowed for automatic sensing of spatial and temporal aspects of team coordination. Sociometric badges meant to track physical activity, speech activity, face-to-face interaction, and physical proximity have been utilized within the context of a post-anesthesia care unit to identify the group's perception of workload, difficulty to obtain information, quality of group interaction, productivity, stress, and the average patient recovery time and daily number of delays (Olguin et al., 2009). However, despite the cost-effective and real-time capture of team coordination processes, there are

limitations associated with IoT sensors and sociometric badges that need to be acknowledged, including the quality of spatial resolution, sensitivity of distance detection, and architectural constraints which can all influence sensor accuracy (Feese et al., 2014). Table 2 offers a summary of data.

Table 2. Review of data sources and team/MTS constructs measured.

| Data Stream  | Team/MTS Construct Measured                              | Citation   |
|--|--|--|
| Spatial - Amount of physical activity                      | Effort   | Feese et al., 2013                                     |
| Spatial - Intensity of physical activity                   | Effort, Effectiveness (length of patient stay)           | Feese et al., 2013; Olguin et al., 2009                |
| Spatial - Variability of physical activity                 | Effort   | Feese et al., 2013                                     |
| Temporal - Time of arrival on-site                         | Performance  | Feese et al., 2013                                     |
| Temporal - Entry into building                             | Performance  | Feese et al., 2013                                     |
| Density of temporal and spatial activity alignment network | Coordination   | Feese et al., 2014                                     |
| GPS  | Coordination, Effort                                     | Feese et al., 2013; Olguin et al., 2009; Current study |
| Speech Activity  | Coordination   | Feese et al., 2014                                     |
| RFID device personnel tracking                             | Situational awareness                                    | Kranzfelder et al., 2011                               |
| Barcode registration for automatic instrument detection    | Situational awareness                                    | Kranzfelder et al., 2011                               |
| Face-to-face interaction time                              | Effectiveness (length of patient stay, number of delays) | Olguin et al., 2009                                    |
| Proximity  | Effectiveness (length of patient stay, number of delays) | Olguin et al., 2009; Current study                     |
| Video analysis (grounded in Activity Theory)               | Verbal and nonverbal communication                       | Battista & Sheridan, 2014; Current Study               |

Although we can unobtrusively measure heart rate, physical proximity, speech activity, and much more, behavioral data offer challenges including the reliability and validity of the data, the sensitivity of the measures, the ability to access the data once it is collected (e.g., consumers cannot access metadata from most popular step, heart rate, and sleep trackers), and the ability to easily align multiple data streams. All of these issues come before trying to make conclusions about team and MTS implications. Thus, we suggest several ways to make decisions about data ahead of time to avoid these challenges.

## MAKING DECISIONS ABOUT SIMULATION DATA

Generally, data are gathered throughout an entire simulation, without a focus on which inflection points and performance episodes are most important to capture. Team training scenarios, especially those operating within the context of an MTS, are characterized by their complexity and fast pace, posing problems for performance evaluation and feedback. *Event-Based Approach to Training* is a methodology often used to design simulation exercises, focusing on the importance of predetermined events (Fowlkes, Lane, Salas, Franz, & Oser, 1994). Having predetermined events makes observing, recording, and evaluating performance against a criterion easier for assessors (Johnston, Smith-Jentsch, & Cannon-Bowers, 1997). *MTS inflection points* are moments of intense between-team interaction, critical for a successful response to the incident. Within the field of mathematics, an inflection point is understood as a point on a measurement curve at which the sign of the curvature changes (Bronstein, Semendyayev, Musiol, & Muehlig, 2004), and due to their criticality, these particular parts of the performance episode should be preordained and scrutinized at finer levels of granularity.

Even ‘objective’ data (e.g., sensors and behavioral analysis) are still a *proxy* for whatever is intended to be measured. For example, we use heart rate to indicate stress, verbal communication between teams to indicate boundary spanning, and physical proximity to indicate coordination (see Table 2). It is of primary importance to test data sources ahead of time, make a priori decisions about data analysis, and use multiple measures to represent the same construct for validation.

However, there may be a point in a simulation when everyone’s heart rate spikes for a few moments. One might assume when analyzing the data that there must have been a stressful interaction between the component teams, but what if there was a large crash of thunder at that exact moment? Onnela and Rauch (2016) provide the analogy of a digital phenotype. Similar to biological genetics, several different genotypes may produce identical phenotypes. Thus, a crash of thunder and a stressful team interaction may create the same graph of team member heart rate monitor data.

### **Using Inflection Points to Test Data Integrity**

Lewin (1943) tells us, “There is nothing so practical as a good theory.” Even (and *especially*) with real-time data, it is critical to a) make a priori decisions about data analysis based on expected moments in a scenario and b) to use multiple data streams (e.g., videos and heart rate sensors) to get the most accurate understanding of the data collected. Protocols are excellent tools to make decisions about data analysis and visualization ahead of time. They identify and describe *inflection points* including when particular actions are supposed to occur, and who is supposed to be involved. For example, in trauma bay simulations, the simulation operator has a checklist of activities and marks down when and how they occur during the simulation. Timestamping these moments allows for an informed decision regarding which moments of data to hone in on during the after action reviews, such as the critical handoff interaction (Riesenberg, 2012). The key is to strike a balance between collecting various sources of data and being able to visualize the most meaningful data quickly and effectively.

Even after acknowledging that sensors are proxies for psychological and behavioral constructs, it is generally assumed that the data provided by the sensors are accurate and aligned with the other streams of data. Data integrity has become a major issue, particularly throughout the rise of real-time data. However, technology does not always work in the way it is expected to. For example, each sensor may have a different sensitivity to what is measured. Data validation is a critical step in the requirement engineering cycle, and includes verifying the correctness and consistency of the data (Berkovich, Leimeister, & Krmar, 2009). Concentrating on inflection points can also be used during the validation process, by allowing engineers to compare the various data streams during a specific segment of an event where the data has a clear range of expected values.

Moreover, inflection points can be considered as moments of between-team interaction in MTSs. These moments are important because they directly impact the outcomes of a situation. Additionally, since MTSs are seldom trained together, highlighting these moments of interaction during after action reviews is imperative for MTS learning and improvement.

## **METHODS AND LESSONS LEARNED**

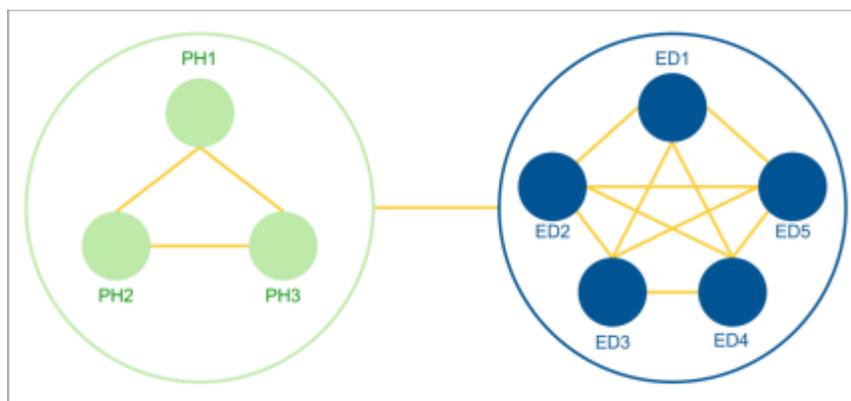
### **Case Study 1: Healthcare MTS**

The first simulation run was comprised of two teams: a *pre-hospital emergency response team* responsible for quickly arriving on scene, getting the victim to the hospital, and recording specific information to transfer to the emergency department (e.g., pulse, blood pressure; see Table 1) and an *emergency department team* responsible for making a quick decision as to whether the patient needed to be transferred to the operating room (Figure 1). Together, the two teams were responsible for working together to make split second decisions about the patient to ensure their wellbeing.

During the healthcare simulation, each participant was given a proximity sensor, which tracked how far they were from the patient, as an indicator of between-team coordination when members from both teams were close to the patient (see Figure 2b). Since this was an MTS scenario, being able to visualize who was near the patient helped us to identify whether a single team was working alone or the two teams were working together. By pairing the proximity sensor data with the physical contact with the simulated patient identified from the video (Figure 2a), we confirmed that when individuals were near the patient, they were indeed working interdependently. Interestingly, Figure 2a and Figure 2b begin at the same time, but the time stamps in the two data streams differ, which is a common and major challenge when working with multiple forms of data collection.

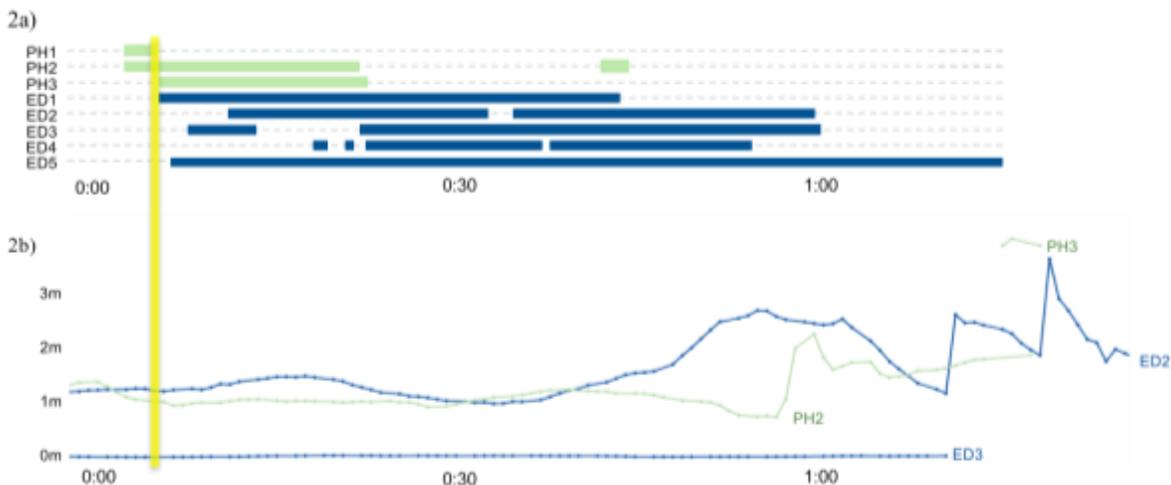
Although the two teams must communicate several times throughout the scenario (e.g., calls from the ambulance not pictured), patient handoff is the most critical moment of the MTS interaction. Several individuals from both teams had overlapping physical contact with the patient throughout the handoff, and at least three individuals (ED2, ED3, and PH2) were within one meter of the patient for the first minute of the handoff which insinuates that the two teams were likely working together to get the patient set up in the trauma bay while sharing information about the status of the patient.

Additional analysis of between-team communication patterns demonstrated the existence of a shared mental model (Kozlowski & Ilgen, 2006), implying that the plan for how to handle the patient was clear to members of both teams. Shared mental models are a common understanding among team members regarding the task that needs to be performed and the teamwork involved (Converse, 1993). Shared mental models are particularly important in MTS scenarios, especially in teams that do not often train together, as they provide a framework for collaboration that helps eliminate extra steps in communication and inefficiencies during collaboration. The lack of a shared mental model in patient handoff may lead to an increased risk in the *gray zone* (i.e., a lack of clarity about the patient condition between the two teams participating in the handoff (Apker, Mallak, & Gibson, 2007). Thus, shared mental models are a necessity to be concentrated on during MTS training.



**Figure 1. Healthcare MTS Example**

PH = Pre-hospital emergency response team. ED = Emergency department team. This figure represents the interdependence between individuals and teams in the healthcare scenario. Each of the individuals on the PH team is connected with the other members on the PH team. Likewise, all of the ED members are connected. The link between the two teams represents the interdependence during handoff that makes the entire entity an MTS.



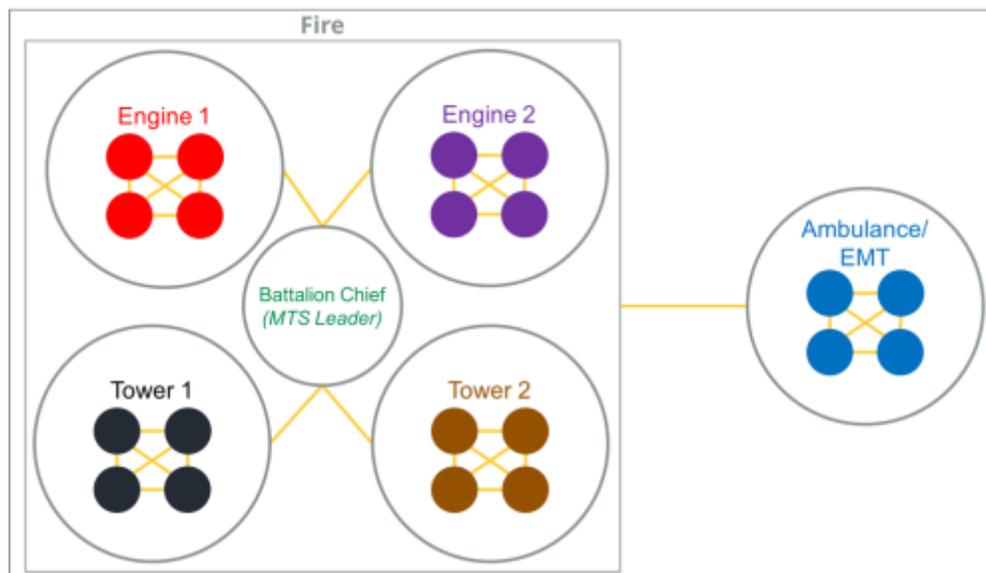
**Figure 2. Timeline: MTS Member Physical Contact with and Proximity to Simulated Patient.**

PH = Pre-Hospital Team (Green). ED = Emergency Department Team (Blue). PH1 = Paramedic. PH2 = Firefighter. PH3 = Driver. ED1 = Respiratory. ED2 = Radiology. ED3 = Surgery Junior Resident. ED4 = Surgery Senior Resident. ED5 = ED Physician. Figure 2a represents the physical contact, coded using video data, between the individual and the patient during handoff. Figure 2b shows the same timeline using proximity sensor data, where the Y-Axis represents the number of meters the actor is from the patient. The yellow bar represents the start of the inflection point of between-team interaction. The two data streams (i.e., video and proximity sensors) did not begin at the same time point, so both graphs were rescaled to show the same timeline.

### Case Study 2: Fire and Rescue MTS

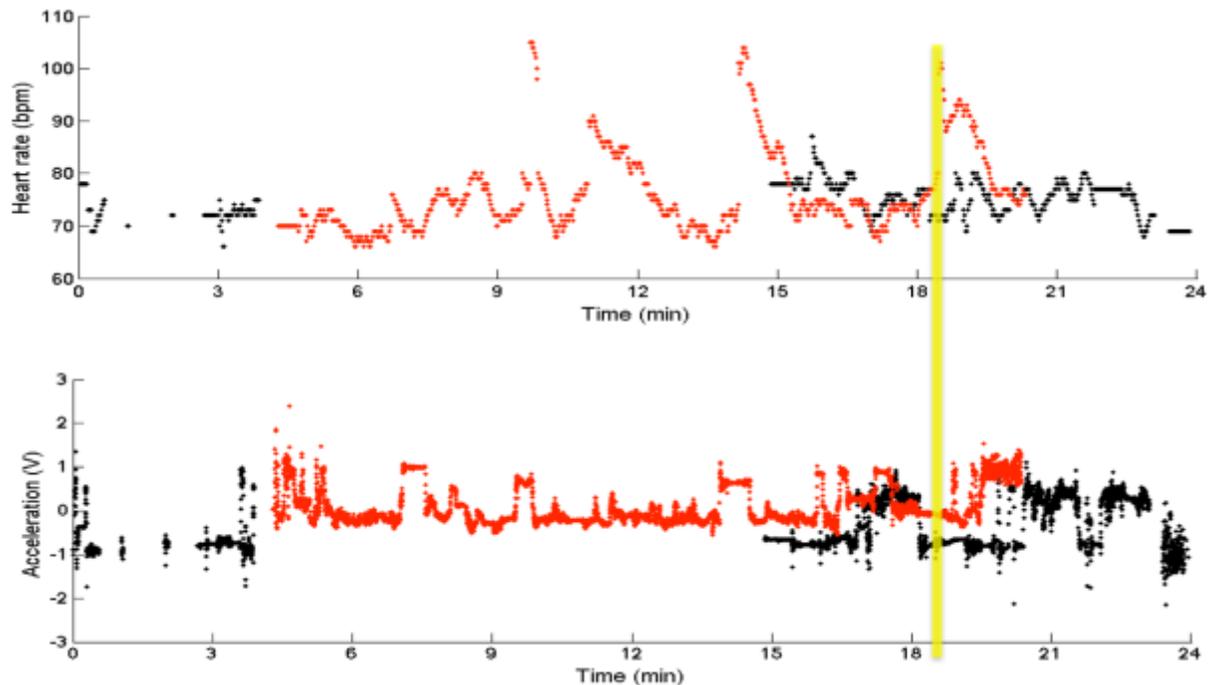
As a second case study, two simulations were run with a large Fire and Rescue department. Data streams included proximity sensor beacons, GPS, audio, video from the actor's point of view, heart rate, acceleration, and skin temperature. The Fire and Rescue department generally sends two Towers (with ladders) and two Engines (with water) to the scene, plus a Battalion Chief to act as the MTS leader, along with at least one ambulance equipped with EMTs who are responsible for taking care of victims once they are out of the building and transferring them to the hospital (Figure 3). The truck and engine teams are either responsible for opening access points to enable entry into the building to remove gas/smoke, controlling and extinguishing the fire, or finding and recovering victims within the structure.

During this case study, we collected heart rate and wrist acceleration data from two MTS members (one from an Engine team, and one from a Tower team). As can be seen in Figure 4, the two individuals followed similar patterns in both the speed of their movement and their heart rate, particularly around the minute 18 of data collection. These similar patterns indicate an inflection point of a shared orientation and common attention to at the same time point. Video data was also collected throughout this simulation, but the smoke created in the building and the sounds of the trucks made it nearly impossible to see or hear what was going on, let alone which teams were coordinating. However, the video did show several moments between-team interaction and coordination before the teams even entered the building. In future work, we aim to collect IoT sensor data from a greater number of individuals in the simulation, and to help mitigate some of the challenges associated with the fire environment.



**Figure 3. Fire and Rescue MTS Example**

This figure represents an example of the teams involved in a fire and rescue MTS. The two Engine teams are responsible for providing water, while the two Tower teams provide rescue assistance and ladders. All four Engine and Tower teams report to the Battalion chief. Once a patient is safely removed from the building, he/she is handed off the Ambulance/EMT team.



**Figure 4. Heart Rate and Acceleration of Engine (Red) and Tower (Black) Firefighters**

This figure indicates an inflection point during coordination between a member of an Engine team firefighter and a Tower team fire fighter. Around minute 18 the two individuals have a spike in both their heart rate and their acceleration. When compared with video data, it can be concluded that these indicators show partial evidence of coordination between teams.

## DISCUSSION

Emergency response scenarios often require multiple teams to come together to solve a single problem. When these MTSs act without any prior training focused on the entire system, as opposed to individual team training, there is an increased risk of information not being handed off efficiently or correctly and teams competing instead of collaborating. Unless MTSs develop shared mental models with a common understanding at all levels, including the purpose of each individual role as well as each team in solving the crisis at hand, accidents and avoidable casualties will continue.

Behavioral data analytics can play a key role in making MTS training possible. First, if between-team interactions are identified as inflection points, the data collected during those time periods can be immediately leveraged during after action reviews, without the noise of the extra data collected throughout other parts of the simulation or event. Real-time data is a powerful tool to be used for the enhancement of MTS training. However, the challenges and potential errors in data collection must be considered ahead of time to increase the reliability and the efficacy of the training developed.

## KEY TAKEAWAYS

- 1) Multiteam system training, as opposed to team training, requires a stronger emphasis on boundary spanning and how to coordinate, collaborate, and communicate with the other teams in the system. Various technologies can be used to assess the quality and efficiency of those interactions.
- 2) Inflection points (e.g., specific actions that must be completed, moments of major change, and periods of between-team coordination in MTSs) are a great way to make decisions ahead of time for data analysis and data visualization, enabling the immediate use of data in after action reviews. Predetermined inflection points also allow for the assurance of data integrity, by allowing you to map the data collected onto what was expected to happen.

3) Even objective data measured perfectly is still a *proxy* for constructs of interest, and data integrity cannot be assumed when using technology sensors. To ensure the accuracy of the data coming from proxy measures it is best to a) use a video backup, b) conduct multiple simulations and compare them to one another, c) use multiple constructs for the same construct (e.g., using proximity, heart rate, and acceleration all as indicators of coordination), and d) compare simulation/event data to the “ideal” situation (e.g., compare to protocols).

4) Time synchronization between multiple technologies (e.g., between video and sensor data) can be a major issue. To compensate for this problem ahead of time, a specific time point can be identified at the beginning of the scenarios to synchronize all channels. This can be done by indicating the military time at which each device started collected data. For video streams, all cameras can be pointed at the same object at the start. As long as the method includes picking a distinctive moment at which all streams can later be aligned, the time synchronization problem should be mitigated. Additionally, choosing technologies that report time stamps, not only of the start and stop time, but also the time of day, can significantly ease handling this problem.

5) While using video, sound recording, and physical sensors in simulations or live scenarios, it is essential to find unobtrusive data streams. Of note, while a single band the size of a watch may be unobtrusive, requiring a participant to wear seven bands at the same time can be highly intrusive. To avoid this problem, it is important to choose technologies that collect multiple data streams simultaneously (e.g., heart rate, skin temperature, acceleration, and GPS all in one).

6) GPS is a great way to accurately indicate where multiple individuals are during a scenario. However, GPS does not always work. Similarly, many proximity beacons rely on a Wi-Fi connection to send data back to a receiver. Many of the situations of interest, including trauma bays in hospitals and burning building, will not have a strong signal, or any signal at all. Therefore, it is important to choose sensors and measures that are compatible with the environment where data is being collected.

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