Embedding Cyber-Physical Systems for Assessing Performance in Training Simulations

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ABSTRACT

As a result of next-generation networking and the Internet of Things (IoT) technologies, big data analysis is possible and has been shown to have a positive impact on areas of national significance yet requires new tools to deal with the variety and quantity of data multiplying at an exponential rate.. Concurrently, IoT technologies are rapidly becoming a mainstream data source. Training simulations have historically been limited either to computer-based simulations or live human-observable field-based simulations ;however, IoT technologies can open up innovative, hybrid digital-physical opportunities both for delivering and for understanding the outcomes of training in a much more dynamic and comprehensive way. The feasibility of IoT technologies in training has historically been limited by interoperability and scale. However, Advanced Distributed Learning's Experience Application Programming Interface (xAPI) allows interoperability and scale in next-generation training environments and provides a way to standardize the formative data of human experience captured through digital context. It also provides a way to capture information and formalize human experience from multiple and varied networked devices into standardized, human-readable statements. These can inform both human and machine learning through leveraging big data analysis and interoperability of the IoT technologies. By leveraging the xAPI and IoT technologies as a cyber-physical system embedded in virtual and live training scenarios, it is possible to capture and measure real-time team performance for immediate analysis and remediation or for post hoc analysis in after action reviews. This paper discusses the application of learning analytics and design for an IoT context through describing the implementation of 1) a live action medical simulation as part of the Global Smart Cities Challenge (sponsored by the NIST and the OSTP) and 2) the proposed capture and analysis of communication performance data and measures within specific coalition training scenarios supporting the 2015 Bold Quest Assessment sponsored by the Joint Fires Division of the Joint Staff.

ABOUT THE AUTHORS

Dr. Shane Gallagher works for the Institute for Defense Analysis and is supporting the Advanced Distributed Learning (ADL) Initiative as a learning scientist. Shane received his Ph.D. in Instructional Technology from George Mason University and MA in Educational Technology from the University of New Mexico. He has led research projects in cognition and game design and R&D projects in learning object content models, simulations, reusable pedagogical models, organizational readiness, and knowledge management. Dr. Gallagher provides learning science oversite for applied research projects, and directs research on video game design for cognitive adaptability and learning science implications of the design of the xAPI. He is also researching methods to apply the xAPI and its syntax to describe social learning interactions and human performance, learning micro-strategies, and gaming micro-puzzles. He has been recognized by NASA for his work on assessing the Johnson Space Center on knowledge management readiness by the JSC Chief Knowledge Officer and has authored papers and chapters on neuroscience, cognition, game design, and innovative learning technology applications and specifications.

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INTRODUCTION

Team performance is dynamic and requires the cohesive interaction and the heightened awareness of numerous individuals participating in coordinated action in response to a continually changing task environment (Weaver, Salas, Lyons, Lazzara, Rosen, DiazGranados, Grim, Augentstein, Birnbach & King, 2010). Practice-based activities such as high-fidelity simulations that afford this type of dynamic interaction are key to developing teamwork skills (Salas, et al., 2009). Medical and emergency response teams are required to quickly comprehend a complex array of factors including time, situational awareness, coordination of team/individual actions, as well as manage physiological stress, any of which can impair performance in high stakes situations (Arora, Sevdalis, Nestel, Woloshynowych, Darzi & Kneebone, 2010). Correspondingly, team training has become a focus in medical and emergency response contexts due to evidence for improving patient outcomes with attention placed on situational awareness, team coordination of activities, and leadership behaviors in realistic medical simulation training (Salas, et al., 2009). However, what can be learned from these complex simulations is often limited by the attention, memory, and knowledge of the facilitator in debriefing the team concluding the realistic, complex, and fast-moving scenario. Although the use of simulation in healthcare training has been shown to improve patient outcomes, there are conflicting results in participants' perceptions of the degree to which simulation learning transfers to actual changes in practice and few reported objective measures of behavior in the clinical environment **(**Cumin, Boyd, Webster & Weller, 2013)**.**

Sawyer and Derring (2013) advise that "post-simulation debriefing is a critical component of effective learning in simulation-based healthcare education" (p.388). The team-debrief concluding a simulation scenario connects the dots in learning from the exercise in attempting to address identified performance gaps. The process of "...reflective observation, facilitated during post-simulation debriefing is a key component of the experiential learning cycle" (Sawyer, et. al., 2013, p.388). However, there seems to be no consensus regarding the optimal format for post-simulation debriefing and little information on how to skillfully and purposefully facilitate the debriefing discussion (Sawyer, et. al. 2013).

Situational Awareness is integral to team performance especially in high stress environments such as the military (Murray, Ensign, & Yanagi, 2010) and emergency medical operations. Team situation awareness (SA) has also been shown to enhance team performance in simulation contexts (Salas, 2009). Endsley (1995) defines situational awareness as "reception of the elements in the environment within a volume of time and space and the comprehension of their meaning, and the projection of their status in the near future" (p.36). Salas, et al.,(2009) similarly state: "The accuracy of an individual's situation awareness is the degree to which a component of knowledge in an individual's SA represents the external environmental reality. The completeness of an individual's situational awareness is the degree to which knowledge in individual's situation awareness captures all or only some of the critical environmental factors (p.350). Murray, Ensign, & Yanagi (2010) simply state it as "knowing what is going on around you."

Through fine grained data collection of targeted activity across individuals, devices, and objects in a team-based, real-world simulation context as well as the dynamic, detailed analysis of this information in real-time, the potential exists to transform simulation team training and better manage resources for learning and performance in emergency response teams and military contexts. This can ultimately result in improving healthcare and military readiness. In addition, targeting the goal of enhanced learning from the simulation team debrief can potentially address variables such as situational awareness and coordination of team actions which the cyber-physical system will be designed to directly address. Enhancing these team behaviors will help to improve team performance across multiple contexts ultimately improving outcomes and impact.

As a result of next-generation networking and the Internet of Things (IoT) technologies, big data analysis is possible and has been shown to have a positive impact on areas of national significance yet requires new tools to deal with the variety and quantity of data multiplying at an exponential rate. (Pal & Saini, 2014). Any resource such as a learning action or path as a service can be encapsulated by a software object that can be discovered and integrated into high level analysis (Mambretti, Chen & Yeh, 2013). Concurrently, IoT technologies are rapidly becoming a mainstream data source. In the space of medical and military training simulations, which have historically been limited either to computer-based simulations or live human-observable field-based simulations, IoT technologies can open up innovative, hybrid digital-physical opportunities both for delivering and for understanding the outcomes of training in a much more comprehensive way. However, two aspects have limited the feasibility of IoT technologies in training: interoperability and scale.

Interoperability is a core challenge for the networked computing research community and for simulation training and learning analytics research. Workplace, in-situ training simulations present significantly complex situations for observing, collecting, and analyzing massive amounts of data generated across people, devices, actions, and contexts; while the hybrid digital-physical simulations also produce voluminous amounts of data. Little to none of this data is normally connected throughout a unified network system and therefore, lacks the fidelity of a standardized, interoperable data format and the necessary common data ontologies which would provide for extensibility and for deep analysis. For these reasons, this research required a system leveraging an open interoperable specification that addresses the dynamic collection of data from the unique combination of digital and physical activity occurring across several medical simulation contexts. It also needed to standardize data across formats in a common and extensible format query-able within a cloud-based scalable immutable database. A scalable solution with these requirements offered the potential to address other real-world collaborative learning and team-based simulation contexts through iterative refinement to collect and analyze experiential data in real time at a massive scale and to significantly contribute to research in advanced networked systems and training simulations.

Two domains where it is imperative to learn from human experience is in medical emergency and military team training such as joint air-ground operations. Learning from applied experiences and working as a team are critical components of a safe healthcare system and of a well-trained and ready military. Simulation-based training holds significant promise to reduce errors and promote performance improvement in high-stakes, high criticality situations. Simulation is a highly complex intervention (Haji, Da Silva, Daigle, and Dubrowski, 2014). However, simulation team training is only as effective as the learning that results and research studies indicate that most of the learning occurs concluding the simulation in the debriefing process (Sawyer & Deering, 2013). Facilitating reflective observation on individual and team performance factors concluding a complex simulation is key for the experiential learning cycle that promotes active reflection and revision of mental models for future beneficial actions and experiences (Sawyer et al., 2013).

This paper describes a proof of concept study leveraging the Advanced Distributed Learning Initiative's Experience API Application Programming Interface (xAPI) specification across multiple technologies. Standardized experiential learning data (e.g. location, proximity, event and time) were dynamically collected and displayed in real-time as well as post hoc. This provided the opportunity for in-process decision making and after-action reviews which allowed us to increase our understanding of how enhanced information for the simulation debriefing process impacted emergency medical team training (and potentially team training in other contexts). Through dynamic, detailed information on specific human activity with devices and objects captured with the xAPI specification during and concluding a complex, fast moving, high-fidelity medical simulation, it was postulated that this system would provide a new window into the how and why of training outcomes as well as informing research in advanced networked systems.

Usage of xAPI

xAPI embedded in simulation-based team training provided the potential to close the gap between simulation and real-world medical practice by collecting detailed objective data thereby allowing a closing of the gap between task performance and feedback by immediate review of that data (McGaghie, Isenberg, Petrusa & Scalese, 2010). The xAPI system provided a standardized format for data collection and analysis used in post-simulation debriefing with the additional benefit of the ability to share data across other simulation contexts for research purposes. As the similarities between decision making under stress by both emergency responders and the military have been well documented (Davis, 2010), this potential should easily be transferred to military training contexts.

xAPI coupled with a learning record store (LRS) was chosen as a basis for this interoperable system. The result was a system that leverages a web service approach to capture contextual ad-hoc simulation participant activity data across complex team-based healthcare simulations storing these data in a cloud-based learning record store (LRS) and establishing a cloud-based analytical environment for research access to captured data in and across teams. The system provides open access to developed architectural components and was initially designed to address potential research questions evaluating the effectiveness of the tools and querying the descriptive data related to pedagogical questions/aligned activity operationalizing constructs such as situational awareness, teamwork, team coordination and stress levels in and across high-fidelity, multi-team simulation contexts. Combined with third party reporting and analytics tools such as the LRS, dynamic data storage and retrieval is possible to track and display most any activity online or off-line including interaction with physical objects, medical devices, mobile devices, sensor-based information, location, time, and stress, etc. This actionable data collected dynamically by the system can include individual behavior with multiple objects and across multiple settings and audio reflections/observations, as well as immediate retrieval, analytics and display of collective team behavior and coordination of actions across individuals with overlaid biometric stress levels, time and location data. This data is automatically collected and displayed in human readable English-like statements that can be aggregated and analyzed in multiple ways.

The xAPI leverages the concept of "activity streams" - an open specification (http://activitystrea.ms/) widely used by social media - and is a technology similar to activity streams with special features, functions, and vocabulary for describing activities, interactions and context within learning activities. Built in JavaScript Object Notation (JSON), the xAPI reads and outputs as human-readable, meaningful statements containing a subject-verb-object sentence structure such as: "Jonathan checked blood pressure" which is easily elaborated to "Jonathan checked blood pressure of patient John Doe with results of 120/80." The statement is also machine readable and the xAPI can be used to track data from any type of networked resource including mobile, sensor, and medical device digital output. The activity stream data is automatically generated and collected in a specialized database (LRS) and can be aggregated and displayed in multiple ways for real-time descriptive analysis and actionable data output for performance improvement.

In this way, it is now possible to track detailed, accurate information about individual and team actions with objects and devices in simulation scenarios that can be compared to their memory of critical factors in the external environmental reality. Reflecting on how complete or how much information each individual is aware of in crisis situations compared to objective data collected by the system could be helpful in measuring and enhancing team members' situational awareness. Accuracy and completeness are important for all three levels of situation awareness: 1) perception, 2) comprehension, and 3) projection (Salas, et al. 2009). Team situation awareness considers much more than just each member's individual awareness; behavioral, cognitive and attitudinal information on team performance are notoriously difficult to measure in complex team simulation environments (Rosen, Salas, Wilson, King, Salisbury, Augenstein, Robinson & Birnbach, 2008). At present, there has not been efficient and accurate methods for tracking these aspects in real-time, which opens up a significant opportunity for research in this area leveraging this system.

PROJECT SCOPE AND PARTICIPANTS

The purpose of the project and data collection described in this paper was to address the design of a technology-based data collection, analysis, and display system targeting individual and team situational awareness and teamwork concluding high-fidelity medical simulations in the debriefing process. The project was initially conceived and operationalized as a proof of concept answering the call of the Global Cities Team Challenge sponsored by the National Institute of Standards and Technology and US Ignite, with involvement from the Office of Science and Technology Policy. It coalesced into a challenge project called the Environment for Smart Medical Team Training (https://www.us-ignite.org/globalcityteams/actioncluster/NSkmt5PEY5iTYgweMCPvRd). To guide the research design of the project we posed the following research questions:

1. What are the mechanisms for articulating data requirements for establishing interoperability in and across simulation scenarios leveraging the xAPI/LRS system useful for advanced networking and education and training research?

2. How can the xAPI/LRS system be used to reveal and model functional behavior and actions related to situation awareness of medical teams and across team behavior in a medical emergency simulation context?
    a) How can the xAPI/LRS system inform the cognitive work analysis relevant to fine grain actions recording during the simulation?
    b) How can the xAPI/LRS system inform the Critical Incident Technique[1] to represent and capture data related to understanding the course of incidents in the simulation?
    c) How can the xAPI/LRS system be used for process tracing in investigating situation awareness and teamwork through critical incidents in high fidelity simulation contexts?
3. What are any differences, consistencies and training implications across emergency, medical and surgical teams when incorporating probing events concerning situation awareness that are deliberately designed and embedded in simulation scenarios?
4. What do participants perceive about what happened in the simulation prior to viewing the revised xAPI/LRS system generated data and after viewing analysis of the recorded data the simulation during the debrief specifically related to:
    a) time and location - relative time-stamping of defined intervals and GPS location data
    b) situational awareness - review of aggregated individual's activity data streams with times and location
    c) team coordination - activity stream data aggregated across team members over time/location
    d) stress level - relative heart rate data across time and location
5. What are the best methods for selecting, analyzing and displaying relevant information from xAPI data for immediate review concluding high-fidelity simulations based on what the participants perceive?

The scope of the initial system design and data collection was to begin exploring these questions as we developed and tested a proof of concept. However, during the process useful data were collected and an initial analysis was performed that provided insight into whether these are the right questions and how we might begin to answer them.

Participants

The participants in this project included the volunteer professionals recruited and involved in the emergency response, medical and surgical team simulation experiences. Two teams of approximately 20 professionals participated in the initial simulation and research cycle led by identified consultant subject matter experts, including an emergency response team (Fairfax Fire and Rescue Department) and the medical team (INOVA Fairfax Hospital pre-surgery team). Although, the researchers strove to include as many members as possible to participate in the proof-of-concept initial cycle it was limited in scope. The surgical team (INOVA Advanced Surgical Technology and Education Center surgery team) was initially included but due to scope it was decided they would function as subject matter experts and facilitators to the data collection. As a result, the primary unit of analysis only included the remaining teams (emergency response and medical). In the future, some individual activity data from the participating teams may be aggregated and analyzed against the research questions.

WHAT HAPPENED

On May 21st, 2015 at approximately 9:30 a.m. a call from Fairfax Emergency Fire and Rescue dispatched emergency responders to an emergency medical distress concerning a person in a vehicle. This person was actually a "sim-man" with two Bluetooth proximity beacons and an Android mobile phone embedded inside. The mobile phone had an app capable of detecting Bluetooth signal from other beacons and transmitting xAPI statements to a LRS in the cloud. Also prior to the 9:30 dispatch, all emergency fire and rescue personnel, and specific emergency room and trauma bay personnel had been "tagged" with a Bluetooth beacon. Android phones with the app were strategically placed on the scene, in the ambulance, and the hospital trauma bay. In addition, personnel had been pre-assigned to ride along with the ambulance and carry an I-Pad loaded with another app for collecting specific event xAPI information and another phone for manually capturing specific event data as a backup to Google docs through

[1] *The Critical Incident Technique* is a set of procedures set of procedures for collecting direct observations of human behavior in such a way as to facilitate their potential usefulness in solving practical problems and developing broad psychological principles (Flanagan, 1954).

Zapier (zapier.com). To capture qualitative data for reference and validation of activity, 12 video cameras were used to film all of the events with high fidelity time stamping using B-Line Medical's video capture (blinemedical.com).

As the call progressed, proximity data were captured through xAPI to the Yet Analytics LRS of all instrumented emergency and medical personnel from the perspective of the sim-man. This occurred at the rate of about 1 statement per every second per beacon. There were 20 beacons used for this purpose. Concurrently, the two beacons in the sim-man (two for redundancy) were detected by the stationary (in perspective of the sim-man) phones as the sim-man moved through the real world from car to ambulance to trauma bay. Additionally, specific medical and team response event data was captured manually in the ambulance ride and in the trauma bay through an I-Pad app transmitted as xAPI statements to the ADL LRS. Concurrently with the I-Pad collection, these same event data were captured through the Zapier app that updated dynamically a Google Sheet visible to trauma bay personnel at the hospital. Figure 1 shows the progression of the sim-man through the simulated response.

Figure 1 Progress on the Sim-Man

The simulation ran for approximately 60 minutes. During that time, we continuously collected xAPI statements on the proximity of medical personnel to the sim-man or the proximity of the sim-man to each stationary reader (Android phone). In addition, we collected manually entered statements reporting discrete medical events concerning the "health" of the sim-man and emergency personnel process while in route and in the trauma bay. These statements described such things as heart rate, blood pressure, or when a specific action occurred.

After the simulation was completed, all personnel met in a conference room in the Advanced Simulation Technology Education Center (ASTEC) in INOVA Fairfax Hospital to debrief. This was led by the emergency response team and the trauma team initially as an after action review. Following that, the team discussed the data collection process, how it occurred, what data was captured, and what the data might be used for. This was accompanied by basic visualizations of the captured data stored in the Yet Analytics LRS as well as event data captured through the Zapier/Google method.

Data Collection System

As we investigated the setting and domain of data collection it was apparent that there are many types of sensor and device data that could possibly be collected – all of which could conceivably be collected as xAPI statements. To begin the scoping process, we held workshops with the emergency medical and surgical communities to determine what would be the most doable and the most helpful to collect. This presented us with various timing or stop-watch needs as well as location needs of the patient in relation to the trauma bay arrival. In addition, the collection of specific event and process-driven activities by medical personnel and the automated collection of medical instrument data (blood pressure, pulse, etc.) were deemed very important. Fortunately, the scope issue was resolved by the donation of beacons, Raspberry Pi computing devices, and other computing devices for our use by Radius Networks and Arnouse Digital Devices Corp. This drove the decision to constrain the system to the collection of proximity data as a primary data source.

To begin understanding what could be gained from beacons and computing devices, a hackathon was held on April 17-18 at the Thingstitute Innovation Lab in Montgomery County, MD (http://mcinnovationlab.com/tag/thingstitute/). This produced initial basic concepts for leveraging and coding for beacons and computing devices and produced initial xAPI statement structures. One concept that moved from idea into the simulation was the manual event tracking idea. Not dependent on beacons, it became an evolving idea of capturing contextual event data albeit manually. It evolved into a xAPI system used on an I-Pad and the Zapier/Google system used on a phone.

The architecture was refined to consist of beacons for emitting Bluetooth signals as proximity data, Raspberry Pi's or ADDC BioDigital PC's for Bluetooth readers, and xAPI activity providers. An additional consideration was whether or not to use a computing device as a local LRS for continued data collection when not in range of wifi access. Due to the discovery of coding difficulties in capturing the proximity of the beacons as needed using micro computing devices and the impractical nature of waiting to transmit xAPI to the LRS only when wifi was present, a decision to move to an Android phone app was made. This became the Bluetooth reader and xAPI activity provider leveraging phone connectivity to continuously transmit xAPI data to the Yet LRS. This is illustrated in Figure 4 which doesn't include the tablet xAPI ADL LRS app or the Zapier/Google checklist collection apps.

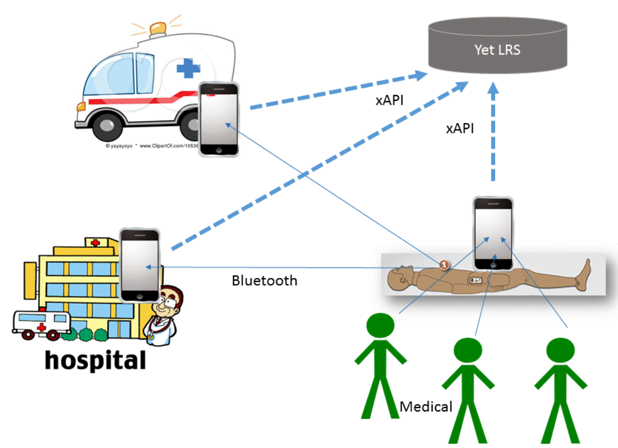


Figure 2 Final Proximity Architecture

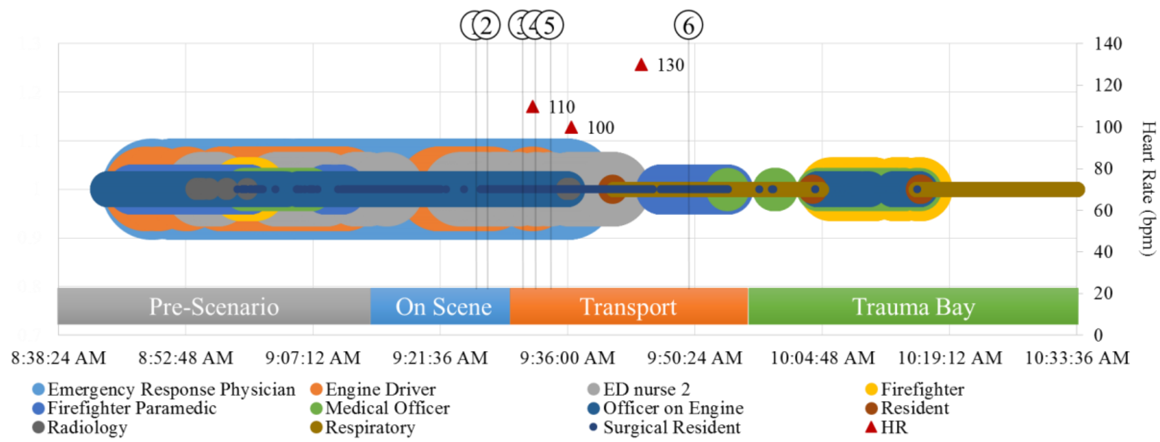
WHAT WE FOUND

During the simulation we were able to collect proximity data at a rate of just over one statement per second as soon as a beacon was detected. All together over 14,000 proximity data statements were collected but approximately 2,000 were preliminary readings. We collected these data from both the perspectives of the personnel to the sim-man as well as the sim-man to the stationary readers. This allowed us to collect and analyze proximity of all 20 tagged medical responders to the sim-man over time. Simultaneously, we tracked the movement of the sim-man into the ambulance, from the ambulance to the ER, and from ER to the trauma bay. Tracking was accomplished at a resolution of ~.66 meter using a function of signal strength changes over time.

Due to time constraints in developing the Android app, xAPI statements for proximity detection were kept to a very low level. The verb "detected" was used when the reader picked up signal from a beacon. The actor in each case was the owner of each phone and is represented by the Google Gmail account from each individual. For example, the sim-man ID is represented by mailto: patrick.shane.gallagher@gmail.com.

The unexpected resolution of the beacon data provided a surprisingly accurate measure of each individual to the sim-man as they came and went. Combining these data with discrete event data captured manually in the other system, events and activity can be combined to provide insight into what actually occurred. By visualizing both data sets, we can determine such things as when the first patient contact occurred and who was present. We know that at 9:25:07 a.m. the patient was put on the back board, it happened on the scene by the emergency response physician, ED nurse 2, and the firefighter paramedic. As the sim-man is moved to the hospital trauma bay, event data show that the patient already has an I.V. established at 9:30:41 a.m. during transport and the patient had a heart rate of 130 at approximately 9:48 a.m. These event data were available in real time to the trauma bay staff through the Zapier/Google app as it was easier to visualize then the xAPI data from the ADL LRS under the team's short development and execution window. The following chart (Figure 3) shows proximity to a Bluetooth reader by role and time, medical events by time, and sim-man proximity to the scene, in transport (ambulance), and the hospital trauma bay.

Other analysis visualizations show the proximity in distance to the sim-man by medical personnel by role as they performed emergency procedures in the trauma bay. For example, the respiratory technician came in close contact to the sim-man/patient during transport, left for about 10 minutes in the trauma bay, returned to the trauma bay and remained in close contact until about 10:35 a.m. then remained more distant until the simulation ended.



1. 9:22:45 AM: First Patient Contact: C-Collar applied
2. 9:25:07 AM: Patient on Back Board
3. 9:29:37 AM: Secondary repeat survey completed
4. 9:30:12 AM: Depart Scene
5. 9:30:41 AM: IV Established
6: 9:48:45 AM: ETA Less than 5 Minutes

Figure 3 Proximity by Role, Time, Event, and Space

CONCLUSION AND NEXT STEPS

The proof of concept was successful in showing that xAPI is a useful tool for collecting and visualizing data from many sources vis-a-vis the Internet of Things. By feedback in the after action review it was determined that this is an extremely positive step forward in improving the overall medical team training and simulation process. Combined with real-time data collecting and visualizations it has the profound potential to move beyond simulation into the operating room. To proceed, it is necessary not only to iterate this process multiple times and refine the system and understanding of the data but to refine the semantics of the xAPI statements and validate them against real practice. The data to do this has been collected via high fidelity video and the coding schemes exist to perform this validation. Our medical partners are willing to support this validation and will continue to work with us to develop verb and activity structures to support this type of contextual data collecting. This represents a deeper dive into the medical team training space.

Another step is to broaden the context from the medical training space to other team spaces with similar high stress environments. One natural progression would be to leverage testbed opportunities within military team training. As ADL is currently working with the Bold Quest project to craft a similar proof of concept in capturing team training communication data during the execution of LVC (live, virtual, and constructive) training missions opportunity lies in embedding xAPI in the data collection process and develop and validate xAPI statements within this environment

Bringing collective capabilities under one umbrella, multinational coalitions are more often coalescing to work on a variety of security challenges (Anderson, 2014). Bold Quest is one such collective capability originally conceived in 2001 as the Joint Staff-led coalition capability demonstration and assessment event. Occurring annually, it provides a repeatable mechanism for military and civilian multi-national, multi-initiative capability development and testing in a coalition operational context (Miles, 2013). For over 10 years, the Bold Quest Coalition Capability Demonstration and Assessment series has provided a realistic venue for joint and coalition members to pool resources, collect and analyze data, and measure coalition effectiveness and interoperability (Anderson, 2014). During last year's event, labeled as Bold Quest 14.2 the Joint Staff-sponsored exercise included about 800 participants from the Army, Navy, Air Force, Marine Corps and U.S. Special Operations Command, as well as Australia, Belgium, Canada, Germany, Denmark, Finland, France, the United Kingdom, Netherlands, Norway and Sweden (Reitz & Seavey, 2014). This year's event began in May 2015 and will run through October with roughly the same number and type of participants.

A critical human component of the project is that of a Joint terminal attack controller (JTAC). A JTAC is "a qualified individual who, from a forward position on the ground or in the air, directs the action of combat aircraft engaged in close air support of land forces" (Joint Chiefs of Staff, 2009). JTACs play a crucial role in the safe and effective integration of air and ground operations. They occupy a position in joint and coalition military services that is at once unique and yet highly representative of many military skillsets: highly qualified individuals performing a challenging set of tasks, requiring regular recertification to provide these critical services during operations (Reitz & Seavey, 2014).

The intent would be to capture the communication activity within coalition JTAC teams in both virtual and live environments. Five initial activities that could be captured in both the virtual and the live environments are 1) report in, 2) report of contact, 3) report of enemy position, 4) report of friendly position, and 5) coordination of movement. This requires the capturing and conversion of Distributed Interactive Simulation (DIS) data to xAPI statements as well as the basic xAPI statement structure as initial first steps. As many of these activities have been historically captured and reported manually, this presents a unique opportunity to provide automated time-stamped binary data of activities representing basic performances. A natural progression would be expanding the data capture and analysis to include audio file attachments and statement structures more representative of the specific activity meaning.

Our goal is to leverage the xAPI and IoT technologies to improve training operations in many critical high stress operating environments and contexts. One logical next step is to test these technologies in a team-based warfighter operations simulation, analyze our results, and if it is successful continue to test and refine facilitating the application to new and emerging contexts.

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