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Adoption of Robots for Disasters: Lessons from the Response to COVID-19

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Adoption of Robots for Disasters: Lessons from the Response to COVID-19

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ABSTRACT

This article describes how robot innovations are adopted during a disaster using the COVID-19 response both as a natural experiment and a case study. The article is based on an analysis of the R4ID dataset of 203 instances of ground and aerial robots in 34 countries explicitly reported in the press, social media, and scientific literature from January 24, 2020, to July 4, 2020, as being used due to the COVID-19 pandemic. While the reports do not provide sufficient detail to ascertain gaps in specific algorithms or specific subsystems, such as perception, manipulation, or autonomy, the size and the pervasiveness of the data permits examination of three questions: 1) how the need for a robot arises during a disaster, 2) whether those needs are met with existing technically mature robots, adapting existing robots, or innovating new robots, and 3) what are the major barriers to

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inserting robots into use during a disaster. The analysis utilizes a novel formal framework consisting of a sociotechnical work domain analysis, an extended demand analysis, and a rating of the technical maturity of each instance using the NASA Technical Readiness Assessment (TRA) ranking. The relative TRA of robots is compared by work domain and modality, followed by an in-depth examination of technically mature Heritage systems, which accounted for 74% of the 203 instances, modified Engineering Systems (13%), and New Systems accounting (13%). The data is also discussed in terms of a) demand pull versus innovation push, b) availability, c) suitability, and 4) risk, leading to a formal model of organization adoption of robotics during a disaster. The analysis shows that organizational adoption of robotics during a disaster embodies two of the four components of the Unified Theory of Acceptance and Use of Technology Model (UTAUT) (Venkatesh *et al.*, 2003), specifically that adoption is primarily influenced by end-users' expectations of performance and how much effort they need to expend to integrate into work processes, also known as suitability and risk. The data also suggests that a third component of UTAUT, facilitating conditions for adoption, occurs during disasters because regulations and acquisition policies may be waived. In addition, the data shows that the lack of availability of some models of existing robots due to low inventory, delays in delivery, or high purchase price facilitated conditions for the development and adoption of new, possibly less reliable, alternative robots. The analysis also shows that the the adoption of robots for a disaster, regardless of work domain, is the result of demand pull by the primary stakeholders, not an innovation push by roboticists, as the majority of missions were established prior to the disaster. The article concludes with four recommendations for roboticists pursuing disaster robotics: 1) work with stakeholders before a disaster to design robots to meet pre-existing established demands, 2) design robots or software that support multi-

ple uses so that robots can be quickly and safely adapted, 3) engage in technology transfer to integrate robots into operational use prior to the disaster, conduct fundamental research into formal methods for projecting the risk of using the robot in terms of direct and indirect performance and consequences, and 4) conduct fundamental research in design and on demand manufacturing so as to increase the availability and functionality of low cost Heritage robots.

1

Introduction

When a disaster occurs, it is natural for roboticists to want to help with the immediate response to saving lives and mitigating societal impacts. Indeed, since 2001, ground, aerial, and marine robots have been inserted into disaster response by emergency response organizations (Murphy, 2014). Case studies of how robots have been used and the specific capabilities of those robots appear in Murphy (2014) and Murphy *et al.* (2016). Speculative articles outlining needed research in specific mechanisms or levels of autonomy are too numerous to cite here. These cases studies generally describe the "what" of the morphological and functional attributes of deployed robot, not the "how" or "why" stakeholders chose one robot over another.

What is missing is an understanding of the overall adoption process by organizations during a disaster and the characteristics of robot innovations that favor adoption. Adoption is a subset of the general responsible innovation process (Nordmann, 2014) by which technologists design and refine innovations for a high social impact application and the pattern of diffusion of innovation in Rogers (2003) describing how adopters decide to adopt a specific technology.

It is more useful for roboticists interested in inserting their robots in a response to understand the adoption process during an emergency rather than the entire innovation and diffusion progression for two reasons. One is that innovation during a response bypasses the responsible innovation process, as only a subset of stakeholders are engaged in the adoption decision and the long-term consequences and effects are not considered. While adoption during a disaster is generally an organizational adoption, not an adoption by an individual who assumes all the risks, the insertion of new technologies for disaster response must fit the response organization policies. The adoption may be local, that is, it may be limited to one unit within a larger organization (e.g., one hospital in a chain) or the decisions may be temporarily driven bottom-up (e.g., one person advocates the adoption for unit or organization).

A second reason is that diffusion of innovation during a disaster similarly compresses or bypasses stages, and may result in only temporary adoption. Indeed, some innovations may be highly experimental and thus not map onto the normal diffusion of innovation process. The initial knowledge, persuasion, decision phases of diffusion are compressed or exceptional due to many influences. One influence is time pressure, as the agency must make a decision quickly without a more nuanced determination or justification, aka satisficing (Simon, 1972). A second is social pressure, as there may be social pressure on the agency to show that are doing something extraordinary to rise to the event. Purchasing costs may not be the primary influence, especially for governmental agencies, as disaster response is often covered by special funds or loans of equipment, though clearly there would monetary limits. Indeed, as noted in Section 2.2, Heikkilä *et al.* (2012) reports that reducing economic costs is not necessarily a predictor of adoption of robotic technology. However, Clipper (2020) reports that health insurers allowing teleoperated robots as a reimbursable cost accelerated adoption for pandemic clinical care. The influence of capital costs is expected to depend on the monetary amount, work domain (e.g., clinical care, public safety, private company), country, etc. Regulations are also not necessarily an influence as most agencies and health care institutions have mechanisms to obtain special dispensation from regulations in emergencies. The final stage of diffusion of innovation, the confirmation/continuation step, is not normally part of the disaster. Adoption of novel technologies is temporary, with no obligation to insert into routine operations or for future disasters. Indeed, Murphy (2014) shows that small ground robots have been successfully used since 2001 for building collapses but have not been adopted into general practice by any country.

1.1 Objectives

Understanding the adoption process can be loosely thought of as answering three sets of questions that appear in UTAUT (Venkatesh *et al.*, 2003) and applications of UTAUT to emergency response (Moats, 2015). The first question is: *How do needs emerge?* Are the use cases with the highest societal impact known to the stakeholders *a priori*, are they uncovered during the incident, or emerge in some combination? The answer to this question provides insight on the drivers for innovation, especially who would identify the use cases (e.g., stakeholders or roboticists), and what sorts of activities roboticists can prepare in advance to contribute to the response (e.g., have existing partnerships with agencies, have certified robot performance for domain D, etc.). A second question is: *How robust and reliable should robots be in order to be adopted?* Is something better than nothing or, as posited in Murphy (2014), robots which reproduce existing capabilities with well understood limitations more likely to be adopted? The answer to this question establishes whether adoption is risk-adverse; if so, focusing on deploying or adapting existing robots may lead to higher rates of adoption than innovating novel robots which are unlikely to be put into service. A conservative adoption process would also imply that more research in needed on projecting and quantifying risk. A third, related, question is: *What are the barriers to adoption during a disaster?* Do regulations or acquisition policies play notable roles? How important is trust by the end-users? While regulations and policies are outside of the control of roboticists, it is helpful to know whether rules can be waived and, if so, under what circumstances. If there are no rules or rules can be easily waived, then this might mean the decision to adopt rests with individual stakeholders, and more research is needed to understand their comfort with robotics.

It should be noted that modeling the adoption process for the response phase is different from conducting a gaps analysis or generating a model of diffusion of innovation as the disaster or disease progressed. An evidence-based gaps analysis is outside of the scope of this article, in part because the majority of the reports generally do not describe specific problems with sensors, mobility, navigation, interfaces, etc. or areas for future improvement. However, as will be seen in this article, the data does support extracting general attributes that influence adoption, especially technical maturity. A model of diffusion would be interesting, exploring questions such as: Was China an early adopter of robotics? Did other Asian countries follow China, then Western countries follow Asia? and Whether adoption of specific robot is influenced by cultural perceptions of robots? But such a time- and culture-based analysis is beyond the scope of this article; instead, this article concentrates on what attributes of the robot itself predict adoption during a disaster.

Until the COVID-19 pandemic, generating answers to these questions has been hampered by the lack of use cases, either for a single type of disaster or for disaster response in general. While Murphy (2014) argues that adoption for the response phase is highly conservative and only robots with a proven record of performance will be deployed, that is a heuristic assessment based on subjective interpretation of only 34 cases in 10 countries from 2001 to 2013.

Fortunately, the COVID-19 pandemic has provided 262 reports in the press, social media, and scientific literature from 24 January, 2020, to 4 July, 2020, of 203 robots being used to respond to coronavirus in 34 countries. The reports clearly cover the immediate response phase in all of the reported countries. These reports are contained in the Robotics for Infectious Diseases (R4ID) open source database at RoboticsforInfectiousDiseases.org. The size and extent of the R4ID database overcomes the previous lack of use cases for an evidence-based model of adoption. Even though the use cases are for a single event, a pandemic, patterns in adoption can be expected to generalize to all disasters, following the "all-hazards" doctrine of emergency operations (Bullock *et al.*, 2011). The "all-hazards" doctrine provides a generic structure for responding to disasters by abstracting the common elements of natural, man-made, or medical disasters.

However, the reports in the R4ID have three limitations which influence the level of detail that can be extracted about the adoption process. One limitation is that the dataset is not guaranteed to be complete. As detailed in Chapter 3, the majority of data collected was from posts in social media and press reports using English keywords. Some instances of robot use were likely not reported, because they were routine or less novel or entertaining, while other more entertaining or surprising uses were more likely to be reported even though they might have less impact on the response. The data may not completely reflect international use, given that 23 of the 34 countries represented in the data had only two or less reported instances during this time period. However, the large number of reports, and aggregating them into a "meta-analysis", offers evidence of general trends in adoption. A second limitation is that the reports are not useful for identifying which robots had a higher impact on the response and examining the adoption process for those high-value uses. The reports typically only describe the robot and how it is being used, often leading with unsupported hyperbole about a particular robot being likely to revolutionize some aspect of the response. Even the articles from robotics literature offer no meaningful measures of impact, possibly because impact is hard to predict or measure without a longitudinal study that examines subtle workplace and economic factors. Therefore this article is restricted to discussing patterns of adoption and barriers to adoption so that robots can be more readily applied to presumably high impact tasks. The final limitation of the data is that the reports do not capture the decision process that led stakeholders to chose a particular robot for a use case. With 203 reports in 34 countries, it is not feasible to conduct follow up interview. Instead, the analysis in this article infers what influenced those decisions from what was, and was not, deployed using a formal analytical framework.

1.2 Approach to Conducting the Analysis

There is no established framework or methodology for explicitly comparing and contrasting the use of robots for different use cases within a disaster. Previous work in disaster robotics, especially Murphy (2014), has focused on comparing robots for a single use case within a disaster. Thus, in order to answer the three motivating questions, this article creates a novel framework for comparison consisting of three components: a *sociotechnical domain analysis* which establishes *how* robots were used, an *expanded demand analysis* which infers *why* robots were used, and the *NASA Technical Research Assessment* which classifies *what* robots were used by their technical maturity. An overview of the framework is given here and detailed later in Chapter 3.

The first component of the approach is a *sociotechnical work domain analysis* which groups instances of robot use for COVID-19 into sociotechnical work domain categories (e.g., clinical care, public safety, etc.) and subcategories of use cases within each sociotechnical work domain (e.g., disinfection, delivery). Since the primary clustering is not by robot capabilities or components (e.g., autonomy, manipulation, sensors), the resulting taxonomy enables a broad assessment of how technology is being used, respective of nuances in implementation between individual models of robots. The clustering based on sociotechnical work domains also helps to clarify what factors influence adoption, for example, a robot being used for clinical care in hospital would have to fit a very different regulatory structure than a robot used to combat labor shortages in a manufacturing plant. The sociotechnical work domains and use cases are described in more detail in Section 3.2.

The second component is a *post hoc demand analysis* to understand whether demand pull or innovation push is a driver for adoption of robots into disasters. Demand analysis is important because if robots for disasters are generally deployed to meet demand pull, then robots can be designed or improved for those missions in advance. Furthermore, if there is an existing demand pull, but robots were not widely available or used, there may be an economic, regulatory, or trust barrier that should be addressed for future disasters. A typical demand analysis is prescriptive, where end-users, regulatory agencies, and developers are brought together before the application of a technology to determine responsible innovation, either where there is a clear demand (demand pull) or the innovation supports new missions or new ways of doing things (innovation push) as per Decker *et al.* (2017). In the case of COVID-19, and other disasters, technology deployment decisions are made rapidly by the primary stakeholder representing the end-users (e.g., healthcare administrators, law enforcement, business owners, etc.), thus short circuiting the prescriptive, broad engagement responsible innovation process.

Rather than perform a prescriptive demand analysis, this article performs a post hoc demand analysis by determining whether the stakeholders used existing, commercially available robots. If so, the adoption was inferred to be driven by demand pull; for example, telepresence healthcare robots already existed before the pandemic and their use increased, thus implying a demand pull for more robots. If robots had to be significantly modified or built from scratch, then it was inferred that there was an innovation push because robotics was being explored as a mechanism for meeting novel missions. The post hoc demand analysis methodology is described in more detail in Section 3.3.

The third component is the use of the *NASA Technical Readiness Assessment (TRA)* methodology (Hirshorn and Jefferies, 2016) to classify the technical maturity of robots. TRA goes beyond the NASA Technical Readiness Levels (TRL) to essentially provide a measure of the *suitability* and *risk* of a technology for a mission within the larger sociotechnical organization. The TRA provides a more useful categorization because a robot can be reliable, work as designed, and be commercially available, thus earning the highest TRL level, but may be difficult to use or have negative consequences on work flows and manpower (Straub, 2015). and thus not truly ready for operations. Thus NASA expanded the device-centric TRL into a larger work domain-centric Technical Readiness Assessment (TRA) classification which ranks the suitability and risk of a technology both in terms of platform maturity (TRL) and usability (Hirshorn and Jefferies, 2016). The TRA classifies technology as *Heritage*, if it is an existing proven technology being applied to a similar mission and work envelope, *Engineering*, if it is a modification of an existing proven technology for a well-defined mission and work envelope, or *New*, involving new hardware, software, a new mission, or a different work envelope. The TRA classification process is described in more detail in Section 3.4.

1.3 Organization of the Article

The remainder of this article is organized as follows. Chapter 2 reviews the related work in modeling the adoption of robots and prior summative of the use of robots for the coronavirus pandemic. Next, the novel framework for analysis is discussed in detail in Chapter 3. Using the data in Chapter 3, Chapter 4 presents the Technical Readiness Assessment of the 203 instances by examining the distribution of Heritage, Engineering, or New instances overall, by the six sociotechnical work domains, and by two modalities (unmanned ground or aerial vehicle). The analysis then goes deeper and considers all Heritage systems (Chapter 5), Engineering systems (Chapter 6), and New systems (Chapter 7). A discussion of the demand analysis, availability, and risk is provided in Chapter 8 resulting in a formal model of adoption. The article concludes with findings for disaster robotics, then uses the model of adoption to make four recommendations for roboticists interested in developing and deploying technology for a disaster.

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