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Contents

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 multiple 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.

2

Related Work

The literature on disaster robotics does not provide a formal model of what factors influence adoption beyond the general heuristics found in Murphy (2014). However, research on robot adoption in surgery, dairy farming, and construction suggests that adoption will be influenced by i) how well the robots work, in terms of performance, human-robot interaction, and the general fit within the existing sociotechnical system, and ii) the risk of damage. There are numerous articles emerging which discuss robots being adopted during the coronavirus pandemic, but these are not comprehensive studies of adoption; however, one study, Mardani *et al.* (2020), did attempt to determine a ranking of factors that might influence the adoption of disruptive technologies such as robots in the healthcare profession for future pandemics. The highest rated factors in decision making were those where the technology matched the needs, such as provided a healthcare information system, or highlighted a risk, such as lack of knowledge of how to apply the technology or concerns over cost inefficiencies. All of the prior work in adoption of robotic innovation are consistent with UTAUT. This article builds on the prior work by incorporating the factors in Heikkilä *et al.* (2012), Marcus *et al.* (2017), Pan and Pan (2019), and Mardani *et al.* (2020) into the analysis under the names of suitability and risk. It goes beyond the prior work to construct an evidence-based analysis of what attributes influence adoption for disasters and thus what gaps should be addressed by research and development.

2.1 Modeling Adoption of Robot Innovation for Disasters

Murphy (2014) summarizes how robots were selected (or rejected) for 36 disasters in eight countries from 2001 to 2013. The selection process during a disaster favored robots i) performing tasks that humans could not do or do safely, ii) with a proven record of meeting the desired functionality in similar work envelopes and iii) that minimized the performance risk, including from operator error due to poor human-robot interaction. This conservative adoption heuristic is consistent with the classic technology acceptance model (UTAUT) posed by Venkatesh *et al.* (2003), which states that the primary influences on how stakeholders choose technology are the perceived usefulness and the perceived ease-of-use. Note that these influences are captured within the TRA ratings, with both the disaster robotics and UTAUT work predicting the most mature technology for an application, i.e., Heritage, will be preferred.

2.2 Modeling Adoption of General Robot Innovation

Adoption of innovation in robotics has been studied for surgical robots (Marcus *et al.*, 2017), dairy farming (Heikkilä *et al.*, 2012), and construction robots (Pan and Pan, 2019) and indicates that usefulness, risk, usability and general fit within the existing sociotechnical system are the primary influences on robot adoption, not economics or advanced functionality. A retrospective of laparoscopic surgical robots found that adoption was a function of economics, whether the robot was useful and reliable, the usability of the robot, and the resistance of the patient to interacting with the robot (Marcus *et al.*, 2017). However, the study noted that the main influences were whether the robot enabled the surgeon to conduct the surgery faster with less performance risk than manual surgery and the impact of the robot on the physical workspace of the operating room. Economic benefit does not appear to be the sole driver for adoption, as a study showed that whether the socio-organizational structure supports new technology had more influence on dairy farmers adopting robot milkers than economic benefits (Heikkilä *et al.*, 2012). Robotics for building prefabrication found that the socio-organizational and work envelope attributes influenced adoption more than the robotic technology itself (Pan and Pan, 2019).

This article examines the R4ID dataset to confirm or deny the conservative adoption heuristic from Murphy (2014) concentrating on usefulness, usability, risk, and work envelope. Validating the disaster robotics heuristic is important since the extreme short time of the response may have meant that availability was the actual primary influence. Available robots were likely those already in commercial existence and thus more useful and usable. This article goes further than UTAUT by documenting and analyzing the source for usefulness (i.e., the demand analysis) and analyzing the influences of availability and risk on adoption during a disaster. It analyzes the use of robots in terms of usefulness, risk, and usability by applying the NASA TRA classifications. It captures usability, work envelope and economic constraints through the sociotechnical work domain analysis.

2.3 Prior Analyses of Robots Used for COVID Response

Five articles by the scientific community have provided surveys of how robots have been used for COVID-19. This comparison is restricted to those surveys that compare and contrast actual robots used for the pandemic. Articles that speculate on how robots might be used or may have technological gaps or deficiencies, or some combination of the above outside of the scope of this article, because they are speculative and do not answer the three questions posed in the introduction

The five articles consist of two papers which discuss use of robots for direct medical functions (Clipper, 2020; Yang *et al.*, 2020) and three about medical and non-medical functions during the pandemic (Murphy *et al.*, 2020; Shen *et al.*, 2020; Strickland and Zorpette, 2020). Of these, Clipper (2020) describes the use of robotics for telemedicine, particularly how approval of telerobotics for temporary reimbursement accelerated adoption. Yang *et al.* (2020), discuss how robots can be used for the medical response to coronavirus, though it briefly mentions what robots had been used to date and that robots can be used for more than public health. Shen *et al.* (2020) provides a survey of 200 reports of robots for pandemic-related uses, concentrating on research opportunities not adoption. The survey did not provide the dataset or how instances were screened for veracity and duplications (in contrast to the formal process described in 3.1, though it appears from what sources that were directly cited that the R4ID dataset contains all of those reports. Murphy *et al.* (2020), provide a survey of how robots were being used in the early months of the pandemic response and argue that the adoption fits the disaster robotics heuristic. Strickland and Zorpette (2020), briefly discuss the type of robots used for COVID-19, but do not go into any detail.

2.4 Comparison

This article differs from those efforts in five ways. First and foremost, the goal of this article is different from Clipper (2020), Shen *et al.* (2020), and Yang *et al.* (2020) because it concentrates on establishing the actual use of robots overall and then using those findings to refine a model of diffusion of robotics innovation during a disaster. Such a model can inform a research roadmap. For example, if perceived risk to the environment is a major influence on adoption in clinical care, then this informs the need for research in explicitly quantifying operational risk in indoor environments with glass walls, clutter along the hallways, and people moving about. However, the distinction is that this article provides data motivating research but does not specify the exact functionality needed. While this article does make recommendations, these recommendations center on what is needed to make robots in general more adoptable during a disaster, not better for a particular mission.

Second, as with Strickland and Zorpette (2020), this article collects and organizes reports in news, social media, and scientific and trade publication about robots for the COVID-19 response; however, this article, following Murphy *et al.* (2020), is limited to those robots that are clearly in use in direct response to COVID-19, have been in use, or are explicitly scheduled for use. This limit is a consequence of the goal of the article to conduct an analysis of the technical maturity of robots directly used in the response and the actual diffusion of innovation.

This article differs from Shen *et al.* (2020) because it uses a formal framework to collect, organize, and analyze the data in terms of technical maturity, as described in Chapter 3. It builds on the sociotechnical work analysis in Murphy *et al.* (2020) but adds the extended demand analysis and technical readiness components. One attribute of the framework is the organization of reports about robots in use for COVID-19 by work domain, with subcategories of functionality for each work domain. This is in contrast to numerous articles discussing robots in terms of robot function (e.g., social robots) or by subsystem (e.g., sensors). While such discussions of functionality and subsystems are valuable, they do not explain why certain robotic technologies are used and others not.

This article differs from Yang *et al.* (2020) and Clipper (2020), which focus on identifying robots in use for a few work domains such as clinical care, by considering applications within a comprehensive taxonomy of six work domains (see Chapter 3). Organizing by phase of treatment may miss insights for robotics for pandemics as well as for disasters in general, given that the R4ID dataset indicates that healthcare is not the primary use of robots, public safety is. The comprehensive coverage of work domains is expected to yield greater insights into the diffusion of innovation process and cross-cutting technologies.

This article differs from Shen *et al.* (2020) and Yang *et al.* (2020) by focusing on technical maturity, not on gaps in terms of specific robot mechanisms (e.g., manipulators) or capabilities (e.g., autonomous navigation). The technical maturity can be established from descriptions in social media and follow up search on the mentioned robot, but accurately projecting gaps requires working with the stakeholders to conduct a full work domain analysis for each mission. Given that the R4ID dataset shows 30 different missions across six major work domains, a gaps analysis is beyond the scope of this article.

This article also differs from Yang *et al.* (2020), which frames the analysis as phases of a disease: prevention, diagnosis, treatment, and recovery. This analysis frames the analysis as phases of an all-hazards disaster, e.g. prevention, preparedness, response, and recovery. Under the all-hazards paradigm, the response phase of an epidemic incorporates prevention, diagnosis, treatment, and recovery, so an all-hazards approach includes medical uses. The all-hazards paradigm offers the advantage of considering the innovation and adoption of robots for non-medical domains and for identifying commonalities across work domains.

3

Data Collection and Analysis Methodology

The analysis depends on the R4ID dataset which is a publicly available spreadsheet of reports of the use of robots for COVID-19 extracting from press reports, social media, and the scientific literature. As of July 4, 2020, 262 reports extracted 203 unique instances of robots used for, or due to, COVID-19, in 34 countries. Each instance was coded with the robot's technical maturity using the NASA Technical Readiness Assessment system (Hirshorn and Jefferies, 2016). The analysis generally followed the constant comparative method (Glaser, 1965). A sociotechnical work domain analysis (steps 1 and 2 of (Glaser, 1965) clustered the instances into six work domains and 30 use cases. The instances in a work domain were subjected to a post hoc demand analysis (steps 3 and 4 of (Glaser, 1965) to determine if existing robots had been in use for those use cases prior to the pandemic.

3.1 R4ID Dataset Collection Process

The R4ID dataset consists of the master set of 286 collected reports that were filtered to eliminate generic discussions, merged to eliminate duplication, then split into 203 instances of a model of robot explicitly used for, or due to, COVID-19. The dataset collection methodology is

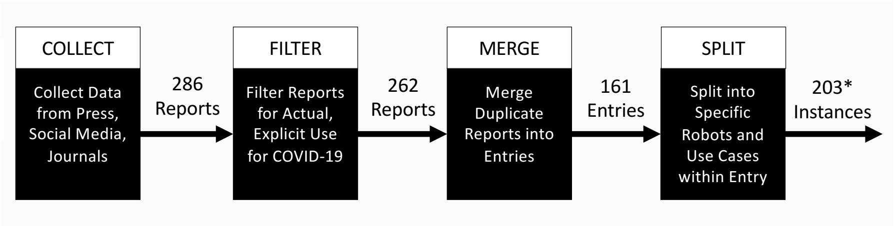

Figure 3.1: Dataset Collection Methodology.

given in the Figure 3.1. The resulting 203 instances captured use in 34 countries, summarized in Table 3.1.

A weekly search was conducted from March 27, 2020, to July 4, 2020, and produced 286 *reports* with January 24, 2020, as the earliest date of publication or of use of the robot, and June 18, 2020, as latest reported date of use in the search period, though duplicative reports continued to surface through July 4. The search used the *Google Search* engine and the *Social Search* and *Talkwalker* social search engines and manual keyword searches of of Facebook, Twitter, YouTube, and LinkedIn as well as in electronic scientific journal databases. The English phrases and keywords used for carrying out the search were: COVID, COVID19, COVID-19 robots, COVID19 Robots, COVID 19 Drone, COVID 19 UAS, COVID Drone, COVID UAS, "COVID-19 and Robots", "Use of Robots for COVID-19", "Use of Robots for the present pandemic", and "COVID-19 Robot uses". While data collection was limited by keywords and phrases in English, "robot" and "COVID" are generally expressed in those words regardless of language. The comments section of the social media posts, and press reports were manually scraped as well to obtain additional links.

Of the 286 reports, only 262 explicitly described an adoption of one or more robots. A robot was considered adopted if the article gave evidence that the robot had been, or was explicitly scheduled, for operational use in COVID-19 related applications. Reports that were limited to general discussions and concerns regarding the robot use for COVID-19 without explicit description of the robot use were excluded. Robots which were built and demonstrated in a robotics laboratory but not operated in the targeted work environment were excluded as speculative, not representative of actual use. Some reports were unclear as to whether the robot was truly in operational use or only in use for a demonstration or a few days. However, if the robot was shown situated in the intended work domain, e.g., in a hospital being operated by healthcare professionals, then the robot was considered adopted regardless of uncertainty over operationalization.

The 262 reports were further filtered to eliminate duplication, resulting in 161 entries. Duplications stemmed from retweeting or republishing of the same report or distinct reports that described the same robot and application. Duplicate reports were merged into a single *entry* in the master dataset. For example, two of the 262 reports repeated a story about the use of Moxi for inventory management at a hospital and these two reports became one entry.

The 161 entries were then split to produce 203 *instances* of *robot model, application* tuples, as some of the 161 entries reported either on multiple robots working independently or multiple use cases for a single robot. Note that if multiple robots of a single model type were being used at the same facility for the same application, e.g., five of the same robot model were being tasked at one hospital for meal delivery, that was treated as a single instance. Reports rarely gave details and thus it was not possible to effectively use the frequency of a robot model in the analysis. If an entry described a robot model being used for different applications, each application became an instance. For example, the entry about the use of KARMI-Bot model described how it was used for three different use cases in a hospital: telepresence for healthcare workers, disinfecting point of care, and prescription and meal dispensing. Thus while the use of KARMI-Bot had one entry in the master dataset, it resulted in three <robot model, application> instances in the dataset used for this article. If the report did not give the name of the robot model, the model name might be manually identified using a photograph or video in the report, otherwise the organization creating the robot served as the model name.

The resulting 203 instances captured use in 34 countries, shown in Table 3.1. The instances are arranged in descending order of total number of robot models. Table 3.1 also shows the number of instances by ground (UGV) and aerial (UAS) modality; no reports in the search period mentioned a marine vehicle.

Table 3.1: 203 Instances of robot use arranged by country with modality

COUNTRY	UGV	UAS	TOTAL
China	38	19	57
USA	35	22	57
India	6	13	19
South Korea	11	0	11
Italy	5	4	9
Singapore	5	1	6
Thailand	5	0	5
UK	1	3	4
Spain	2	2	4
UAE	0	3	3
Ireland	1	2	3
France	0	2	2
Belgium	1	1	2
Turkey	1	0	1
Tunisia	1	0	1
Taiwan	1	0	1
Sweden	0	1	1

COUNTRY	UGV	UAS	TOTAL
Chile	0	1	1
Cyprus	0	1	1
Denmark	1	0	1
Estonia	0	1	1
Germany	1	0	1
Ghana	0	1	1
Greece	0	1	1
Honduras	0	1	1
Japan	1	0	1
Jordan	1	0	1
Kuwait	0	1	1
Lithuania	0	1	1
Mexico	0	1	1
Netherland	1	0	1
Nigeria	0	1	1
Philippines	0	1	1
Rwanda	1	0	1
Total	**119**	**84**	**203**

3.2 Categorization into Sociotechnical Work Domains

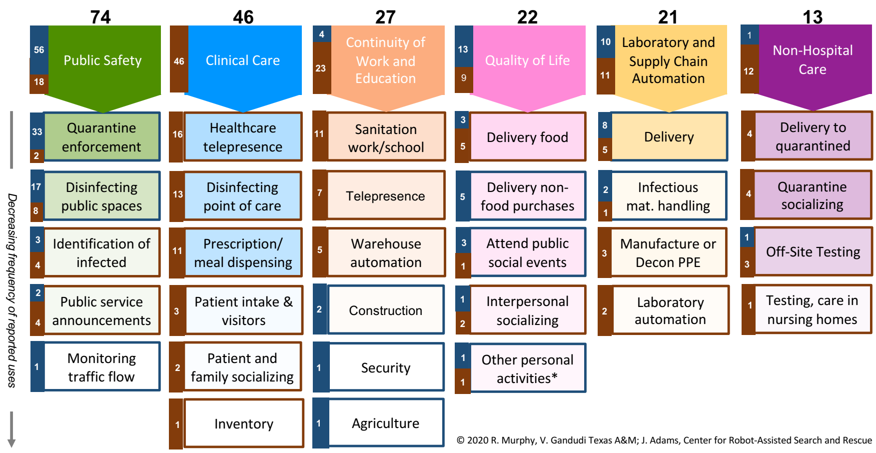

Figure 3.2: Categorization of instances of robot use based on the sociotechnical work domain and by modality. (Brown represents UGV and blue represent UAS).

Each of the 203 instances were assigned to one of six sociotechnical work domains and 30 use cases within that domain, as shown in Figure 3.2. The assignment process followed steps 1 and 2 of the the constant comparative method (Glaser, 1965), where the incidents were iteratively compared and grouped into categories based on distinguishing attributes emerging from the comparison. The sociotechnical work domain analysis converged on six work domains: *Public Safety, Clinical Care, Continuity of Work and Education, Quality of Life, Laboratory and Supply Chain Automation*, and *Non-Hospital Care*. The 30 use cases reflect subjective clusters, attempting to abstract missions or tasks. A use case for one domain may have nearly identical objectives to a use case in another domain, but have different design constraints. For example, delivery of meals in a hospital is similar to delivery of food to citizens in terms of objectives but in the former case the final step is distribution by a nurse's aide to deathly ill patients, whereas in the quarantine facility the citizen and robot can directly interact.

The six sociotechnical domains were differentiated by three technical factors and two social factors. The three technical factors were *work* *domain*, that is, the overarching purpose and function of the application, the types of missions, or *use cases*, that typify achieving the purpose, and the *work envelope* that the robot would be operating in for those functions. The technical factors are common operational design inputs for a robot. The two social factors are the *stakeholders impacting adoption*, including regulatory agencies, and the *worker or interactant skills and expectations*. While workers and interactant are stakeholders and could influence adoption, their influence is typically indirect. For example, the primary stakeholders in adopting robots in a hospital for clinical care are hospital administrators, insurers, and medical regulatory agencies, though it would be hoped that the decision would incorporate feedback from healthcare workers operating the robot and how the robot would interact with patients. Understanding the worker and interactant skills and expectations is important. Consider that a robot being used by highly trained technicians to automate laboratory procedures in a dedicated laboratory without bystanders is different than a robot being used by a nursing assistant with minimal training on robotics to interact with sick, disoriented patients. Note that the social factors impact the usability, and thus the design, of the robot beyond the traditional operational design.

The six work domains are similar to, but different from, the ones proposed in Madurai-Elavarasan and Pugazhendhi (2020) for discussing the societal implications of new technologies for pandemics, including robotics. Those domains were Healthcare System, Government, Public, Industry, Environment, and Energy. The justification for the choice of work domains was not given, but appears to reflect economic sectors. These sectors and description of robotics are too abstract to support the objectives of this article.

Public Safety reflected the role of law enforcement, public works, and public health agencies in carrying out policies affecting the general public; for example, enforcing social distancing or sheltering in place regulations. Technology adoption is influenced by regulations and policies and agency budgets. These activities are subject to regulations and governmental policies and have high public accountability. The interactants are officials operating robots as part of their duties, roboticists acting in an official capacity, or citizens who may have had no prior exposure to robots or to a robot being used in that context.

The use cases and work envelope for Public Safety activities typically occurred in outdoor venues, such as paris; or in indoor venues that were large open spaces such as arenas and subway entrances. As seen in Figure 3.2, the Public Safety work domain had a total of 74 instances (18 UGV, 56 UAS) distributed across five use cases:

- *Quarantine enforcement (35)*: Two UGV and 33 UAS were used for enforcing quarantine measures, social distancing measures, and COVID related surveillance.
- *Disinfecting public spaces (25)*: Eight UGV and 17 UAS were used to disinfect or sanitize spaces usually occupied by general public, such as subways, public recreational areas, urban areas, and airports.
- *Identification of infected (7)*: Four UGV and three UAS were used to identify individuals with COVID symptoms using thermal imaging.
- *Public service announcements (6)*: Four UGV and two UAS were used to carryout public announcements, and convey information that would be useful in assisting and educating the public regarding COVID.
- *Monitoring traffic flow (1)*: One UAS was used to monitor traffic flow.

Clinical Care captured how robots protected healthcare workers while they performed testing and treatment and helped the workers cope with the surge in demand. Technology adoption is influenced by whether the cost of the technology is accepted by medical insurers, governmental regulations, e.g., medical devices, and internal review boards. The interactants are generally healthcare specialists working with ill, disoriented, and often elderly patients through the robot. Janitorial workers would normally control disinfecting robots.

The use cases and work envelope for Clinical Care is typically a hospital or clinic, though sometimes a pop-up clinic in a sports arena or other venue. Clinical Care had 46 instances, all UGV, distributed across six use cases:

- *Healthcare telepresence (16)*: 16 UGV were used to reduce the exposure of healthcare workers by serving as a proxy for conducting diagnosis and acute care of patients. This use case included both non-contact and physical contact tasks.
- *Disinfecting point of care (13)*: 13 UGV were used to sanitize hospitals, affiliated clinics and point of care facilities using UV-C, and disinfectant spraying technologies.
- *Prescription and meal dispensing (11)*: 11 UGV were used to deliver prescriptions and meals within the hospital facilities.
- *Patient intake and visitors (3)*: Three UGV were used to conduct registration, admission and intake related tasks at the front desk of the hospital facilities.
- *Patient and family socializing (2)*: Two UGV were used to enable telepresent social interaction between patients and their families,
- *Inventory (1)*: One UGV was used for grabbing supplies and restocking them within the hospital.

Continuity of Work and Education represents the use of robots by companies or institutions to maintain operations threatened by the loss of workers due to illness or to prevent disease transmission between workers and clients. The robots are acquired as a capital cost. These companies or institutions are not subject to regulations beyond the normal occupational work and safety requirements. The interactants may be workers or teachers interacting with other, students, or customers through a robot but often a janitorial or line worker setting up or controlling the robot.

The use cases and work envelopes for these applications are varied, including the exterior perimeter of facilities and construction sites, indoor classrooms and offices, and indoor but large warehouses. Continuity of Work and Education had 27 instances (23 UGV, 4 UAS) distributed over six use cases:

- *Sanitation at work/school (11)*: 11 UGV were used to disinfect, sanitize and clean workplaces and premises of educational institutions using UV-C, disinfectant spraying technologies, or robots with sweeping capabilities.

- *Telepresence (7)*: Seven UGV with telepresence capabilities were used as proxy of either a customer or a business representative to maintain virtual contact thereby enabling the business to carryout their regular operations without much hassle. In some cases similar telepresence robots were used as proxy of a student, thereby enabling them to attend school events like graduation virtually.

- *Warehouse automation (5)*: Five UGV were used in automating and assisting in operational processes of warehouses and other processing facilities.

- *Construction (2)*: Two UAS were used for assisting with construction related operations such as carrying lighting to enable construction activities at night.

- *Security (1)*: One UAS was used for security related operations and surveillance within a private infrastructure employed by the private entities in charge.

- *Agriculture (1)*: One UAS was used to assist in agricultural activities like night time seeding of crops.

Quality of Life captures how individuals, entertainment, or social organizations use robots. These stakeholders pay for, and operate, robots directly or lease services. The interactants may be members of the public unfamiliar with robots or own personal consumer robots, or robot professional providing a service.

As with Continuity of Work and Education, the use cases and work envelope can be indoors or outdoors. Quality of Life had 22 instances (9 UGV, 13 UAS) distributed over five use cases:

- *Delivery food (8)*: Five UGV and three UAS were used to deliver food from restaurants, groceries, and other consumables to individuals.

- *Delivery non-food (5)*: Five UAS were used to delivery non-food items such as books and medicine to individuals.

- *Attend public social events (4)*: One UGV and three UAS were used to facilitate social events, for example using drones for a public light show to thank front line personnel or enable individual to attend a social event through telepresence.
- *Interpersonal socializing (3)*: Two UGV and one UAS were used to assist in interpersonal socializing of an individual, for example using an UAS to ask a neighbor out on date.
- *Other personal activities (2)*: One UGV and one UAS were used to carryout other miscellaneous personal activities, for example, a citizen remotely walking their dog using their personal UAS.

Laboratory and Supply Chain Automation covers the use of robots to support and assist in healthcare supply chain automation solutions and laboratory healthcare operations in diagnostic laboratories, hospitals, and non-hospital facilities. The robots were adopted either by private laboratory service companies as a capital expense or by a hospital, subject to allowable insurance reimbursement. In general, the interactants were specialists directly operating or working with a robot without an expectation of a social interaction.

The use cases and work envelope could be indoors or outdoors. Laboratory and Supply Chain Automation had 21 instances (11 UGV, 10 UAS) distributed over four use cases:

- *Delivery (13)*: Five UGVs and eight UAS were used to transport testing samples and related equipment between laboratories, testing centers, or clinics.
- *Infectious material handling (3)*: One UGV and two UAS were used to handle infectious or contaminated materials.
- *Manufacture or Decon PPE (3)*: Three UGV were used to decontaminate used personal protection equipment (PPE) kits or to assist in manufacturing PPE kits.
- *Laboratory automation (2)*: Two UGV were used to automate testing and other related laboratory processes to reduce COVID testing time.

Non-hospital Care captured the use of robots for quarantined individuals or for assisted living or nursing homes. These people are not being treated for COVID-19 and thus do not fall under Clinical Care, but their activities or operations are restricted by public health regulations. The costs may be either be paid by a public health or public safety agency managing a quarantine facility or by a private company managing a non-clinical facility. The work envelope is indoors but may be tent shelters, re-purposed auditoriums or sports venue, hotels, or nursing homes. The interactants may be trained healthcare workers using the robot and citizens with and without symptoms interacting with the robot.

Non-hospital Care had 13 instances (12 UGV, 1 UAS) distributed across four use cases:

- *Delivery to quarantined (4)*: Four UGV were used to deliver food and supplies to individuals in quarantine facilities.
- Quarantine socializing (4): Four UGV enabled patients in quarantine facilities and nursing homes to socialize with their remote families and friends through telepresence.
- *Off-site testing (4)*: Three UGV and one UAS thermal imaging capabilities were used to detect coronavirus symptoms in individuals in privately owned workplace clinics.
- Testing, care in nursing homes (1): One UGV was used to provide non-acute care for individuals in a nursing home.

3.3 Post Hoc Demand Analysis

This article conducts a post hoc demand analysis with two objectives. One objective is to identify trends in demand pull or innovation push for disasters. The second objective is to examine the impact of *availability*, *suitability*, and *risk* on selection of robots. The analysis meets these objectives by identifying i) if existing robots were available for a use case, thus implying an a priori demand pull, ii) whether existing or novel robots were used for those use cases, implying that there was a demand pull but some some barrier preventing adoption, iii) if existing robots were used or adapted for novel missions, implying the value of general purpose robots, and iv) if novel robots were used for novel missions, suggesting that roboticists had provided an innovation push to meet an emergent demand that would have gone unmet. The analysis methodology followed steps 3 and 4 of the constant comparative method (Glaser, 1965), delimiting or restricting the parsimony of influences on adoption and the scope of the theory so that it could remain tractable, and then synthesizing the model.

Availability is typically a critical factor in prior disasters; consider that a hurricane, earthquake, or wildfire has a very short opportunity for saving lives and mitigating societal impacts of food, shelter, sanitation, transportation, etc. Due to this narrow window of opportunity, there is generally no time to create a new robot. However, pandemics are long duration events and thus the window goes from days to months, possibly years, thus permitting more opportunities for adoption of innovation. This article explores whether robot deployment strongly follows availability or if the use of available robots was the result of other factors, possibly the suitability of the robot for the mission or the expected risk.

Related to availability is the suitability of a robot to meet demand pull. An existing robot may be available but have to be modified in order to be suitable for the demand. Multiple robots may be commercially available and promoted for the same application, but one may offer a poor user experience or encumber hidden manpower costs, thus a robot may not be widely adopted because it is not suitable for the work domain. This article examines the suitability of robots for COVID-19, inferring suitability from frequency of acquisition. The results are expected to help identify potential areas for research and development.

The risk of deploying a robot during a disaster may be take one of three forms: direct performance, indirect performance, and unintended consequences. The most obvious risk is risk of direct poor performance; for example at the Pike River mine disaster, a ground robot was applied to a new mission and work environment and failed, blocking the only access to the trapped victims (Murphy, 2014). As noted in Murphy (2014) and Straub (2015), primary stakeholders often are concerned with indirect performance risks incurred by unintended impacts on work flows and manpower, resulting in a high cost, low benefit ratio. But stakeholders may face a third risk of incurring negative consequences. One example of a negative consequence is unfavorable regulatory and public reaction; for example, the use of aerial vehicles (drones) for enforcing social distancing in Westport, Connecticut, violated cultural expectations of privacy leading to a public backlash (NBC, 2020). Another example is the use of robots for physical human interaction, where the stakeholder has to decide if the benefits outweigh the risk of injury.

3.4 Technical Readiness Assessment Methodology

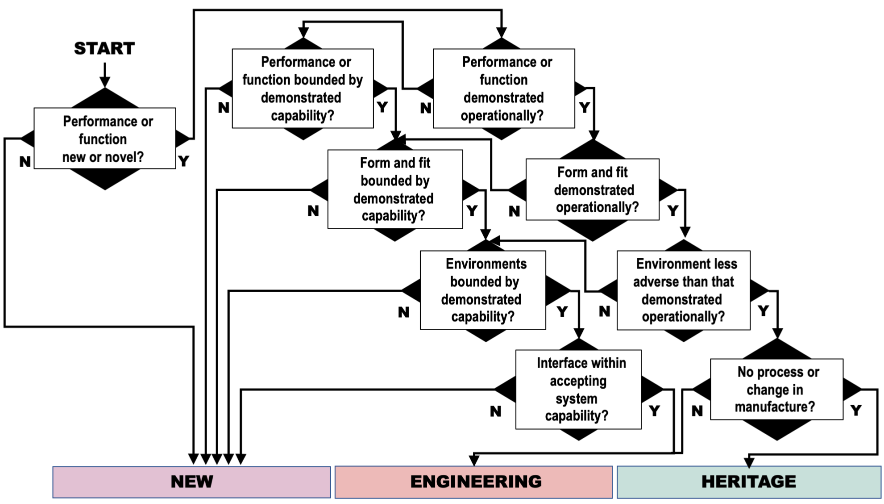

Figure 3.3: Process to classify according to technical maturity, adapted from (Hirshorn and Jefferies, 2016) to be more readable and follow a color convention of pastel green for Heritage, salmon for Engineering, and lavender for New.

The 203 instances of robot use were divided into three categories according to their technical readiness, *Heritage*, *Engineering*, and *New*, based on the NASA Technology Readiness Assessment (TRA) criteria (Hirshorn and Jefferies, 2016). The categories reflect degrees of suitabilty and risk. The process in Hirshorn and Jefferies (2016) is illustrated in Figure 3.3.

- *Heritage:* a technology that already exists, is used successfully in operation, and can be transferred to the new mission without changing its function, fit or form. The existing successful use indicates that the robot has high suitability for the use case and work envelope and poses little risk, either to performance or unintended consequences.

  A technology is classified as Heritage if it satisfies the following Hirshorn and Jefferies (2016):

  - The technology has no change in its manufacturing processes, and
  - The technology has no change or modifications to its function, fit or form when used for a use case, and
  - The environment to which the technology would be exposed to is not more adverse than the ones the technology was originally intended for.

- *Engineering:* a technology whose function or history of performance is well understood and established, but needs low risk engineering modifications to make it more suitable for a particular mission.

  A technology is classified as Engineering if it satisfies the following criteria (Hirshorn and Jefferies, 2016):

  - The technology is neither Heritage nor New, and
  - The development or modifications of the technology requires use of existing components, techniques and processes within demonstrated capabilities or design intentions.

- *New:* a technology with new functions that do not already exist or and has not been used operationally for a particular mission. Thus a New technology can be expected to have gaps in suitability and pose a higher risk because it will likely have unintended consequences for work flow processes and low reliability that would be worked out over time.

A technology is classified as New if it satisfies the following criteria (Hirshorn and Jefferies, 2016):

- The use case to which the technology is used for is new or novel, or
- The use case to which the technology is applied to exceeds its functional capability or demonstrated performance, or
- The form or fit of the technology exceeds its previous demonstrated capability or performance, or
- The technology integration needs exceeds previous demonstrated capability, and
- The technology is neither Heritage nor Engineering.

3.5 Limitations of the Analysis Methodology

The inherent limitations of the dataset were described in the Introduction and are expanded here. In addition, the analysis process itself is limited in that the categorization is subjective, although it follows a well-defined classification process.

The data collected relied on posts in social media and press reports, which means instances were likely missed and certain applications are likely to be under-represented while some are over-represented. The reports tended to have content that focused on novelty or innovation; this means that robots already in use before the pandemic might be less attractive for reporting. Reports favoring novelty would lead to an under count of existing robots for a work domain and use case, while robots that were innovative but unlikely to reflect real trends, such as robot hand sanitizer dispensers made out of Legos, were over-represented.

The data is also imperfect due to the keyword "robot," which appears over-used in the press. Rather than try to derive a single definition of robot, the data collection methodology accepted any posting that labeled the technology as a robot. This means that systems such as the aforementioned Lego robots were included in the dataset, despite questions over their impact. If a report stated that the technology was a robot, it was treated as a robot rather than arbitrate the definition of robot that would capture both a formal engineering definition and the public vernacular.

Another limitation is that, as majority of the search was carried out manually, some of the links were not collected due to the vast data present on the world wide web. The data collected is based on reports rather than a thorough work domain analysis which would require extensive follow up interviews, surveys, etc. Given the large number of reports and the distribution across 34 countries, this is outside the scope of this effort. However, the large number of reports does suggest that the data reflects general trends and leads to useful conclusions.

The data does not provide measures of impact or efficacy, only that a robot was used for a particular application. Because the majority of reports were taken from the press and social media, their content focused on the innovative aspects and not scientific measures of performance and impact. Indeed, it may not be possible to determine the impact beyond the number of robots used for a work domain, as there is no clear definition of impact and measures. Impact could mean lives saved, but other possible metrics are the reduction in the operators' or interactants' workload, economic cost-benefits, and number of stakeholders continuing to use the technology. None of the metrics can be applied to the dataset because the reports generally do not have sufficient detail. However, the size of the dataset allow trends in impact and efficacy to be inferred; for example, a large number of instances for a use case suggests that robots are needed for that use and their deployment have value and an overall positive impact.

Similar to impact, the data does not directly reveal specific algorithms or shortcomings in the technology. The analysis does not assume that just because a robot is used, it is perfectly suitable, reliable, has high usability, and is optimized for the mission. Unfortunately the majority of reports were not detailed scientific analyses aimed for the robotics community, instead they were short descriptions targeted for the general public. Fortunately, the patterns of adoption in the dataset do indicate which missions were the most prevalent, which suggests where further investigation for a use case will likely identify improvements that have a high impact, and the New use cases, where research may be of benefit. As will be discussed in Chapter 8, the data does lead to model of adoption that indicates advances in robotics that lead to on-demand availability and reduce risk are critical regardless of work domain or use case.

The categorization of work domains, use cases, and technical readiness is subjective, though the categorization follows a formal, reproducible process. The sociotechnical work analysis requires a subjective judgment in interpreting the reports and clustering into domains and use cases is subjective. Similarly, there is a clear decision process in Figure 3.3 for determining the technical readiness of an instance, but the decision may require inferring commercial use and suitability for a use case. Fortunately, the large amount of data in the dataset and the use of a reproducible formal process means while the placement of some instances into a particular category may be debatable, the categorization should capture overall trends. Also, it should be noted that the dataset is publicly available and can be examined to find alternative classifications and interpretations.

4

Technical Readiness Assessment by Work Domain and Modality

As shown in Figure 4.1, the overwhelming majority of the 203 instances were Heritage systems, with 150 (74%). Engineering systems accounted for 27 (13%) and New for 26 (13%). Figure 4.2 captures the distribution of readiness for the six sociotechnical work domains, showing that Heritage systems were the majority for all applications. The distribution of Engineering and New innovations appeared to depend on the work domain. Table 4.1 indicates that Engineering and New innovations were not restricted to a particular modality as those instances were almost equally split between UGV (27) and UAS (26). The findings by work domain and modality are discussed in more detail below.

4.1 Technical Readiness by Sociotechnical Work Domain

Heritage was the large majority of instances for each of six work domains as shown in Figure 4.2. The relative size of that majority varied by work domain, with Heritage systems ranging from a low of 65% for Public Safety to a high of 95% for Laboratory Automation.

Only three of the six work domains deployed Engineering systems. Public Safety had the largest use of Engineering systems (23) of any application category, while (Quality of Life, Laboratory Automation,

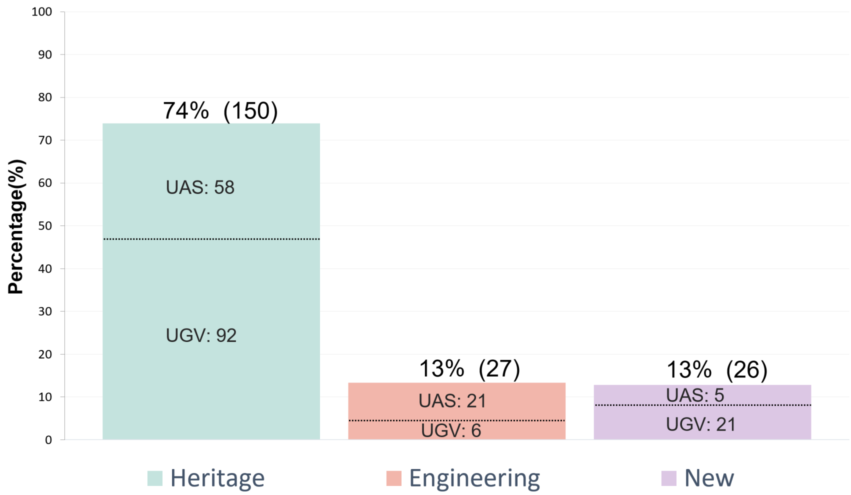

Figure 4.1: Technical Readiness Assessment of all instances.

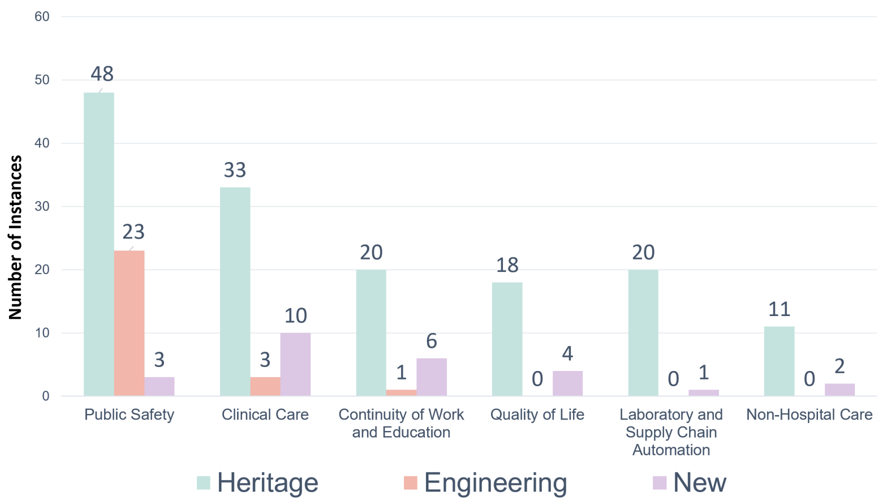

Figure 4.2: Technical Readiness by sociotechnical work domain.

and Non-Clinical Care did not use Engineering systems. The Public Safety Engineering systems primarily relied on adapting small UAS that were built to support interchangeable payloads and provided teleoperation modes of control enabling new missions. The concentration of Engineering systems in Public Safety may also reflect the recent adoption of small UAS by law enforcement agencies and donations by drone manufacturers. The lack of Engineering systems in Quality of Life and Non-Clinical Care work domains may be the result of the lack of existing robots for those market niches; thus any use of robot, even if it were in common use for, say, disinfection, was considered a New system. Engineering systems may have been missing from the Laboratory Automation area because it is a highly specialized and well-established, so any changes reflected New hardware or software.

All six work domains contained instances of New systems, though typically a small number. As would be expected during a pandemic, Clinical Care had the largest number of New instances, 10 out of 46. Three of the 10 instances were truly New system using novel robot hardware and software for the new mission of invasive sampling patients for COVID. The other seven New systems were clones of existing robots, where new hardware was built to overcome lack of availability and costs of existing systems. Laboratory and Supply Chain Automation had the lowest number of New instances, one which was for Laboratory automation use case. The low number of instances is not surprising as Laboratory Automation is highly regulated and the medical supply chain does not favor creative solutions.

4.2 Technical Readiness by Modality

The modality of robot used for COVID-19 related activities was roughly evenly split between UGV (119 instances) and UAS (84). However, the technical readiness of the two modalities varied, with UAS dominating Engineering systems and UGV dominating New systems. As seen in Figure 4.2, which is a visualization of Table 4.1 as a bar chart, UGV and UAS are nearly equal in use for Heritage system, but UAS dominate Engineering systems, and UAS only reflect a small portion of the New instances. UAS may lead in Engineering system because of their intrinsic

Table 4.1: Technical Readiness by sociotechnical work domain and modality.

TRA	Heritage			Engineering			New		
Modality	UGV	UAS	TOTAL	UGV	UAS	TOTAL	UGV	UAS	TOTAL
Public Safety	15	33	48	3	20	23	0	3	3
Clinical Care	33	0	33	3	0	3	10	0	10
Continuity of Work and Education	17	3	20	0	1	1	6	0	6
Quality of Life	6	12	18	0	0	0	3	1	4
Laboratory and Supply Chain Automation	10	10	20	0	0	0	1	0	1
Non-Hospital Care	11	0	11	0	0	0	1	1	2
TOTAL	**92**	**58**	**150**	**6**	**21**	**27**	**21**	**5**	**26**

adaptability without increasing the risk of unintended consequences or decreased safety. Consider that many UAS are built for adaptability even though they are marketed for a specific domain; for example the DJI MG-1P UAS is marketed for precision agriculture but was easily adapted for spraying disinfectants instead of pesticides without any loss of platform safety. While UGV were modified, most were superficial exterior modifications such as adding trays or disinfecting payloads. It appeared that the UGV were designed for specific uses and did not support hardware or software modifications, thus limiting their applicability.

Table 4.1 shows the modality by work domain. UGV were used exclusively for Clinical Care and almost every use case in Continuity of Work and Education and Non-hospital Care. This appears to be driven by i) the work envelope, which is indoors and highly structured built environments with unpredictable clutter, and ii) workplace constraints, especially safety around bystanders such as healthcare workers and patients. UAS were the majority of reported instances in Public Safety and Quality of Life and nearly tied for Laboratory Automation. The heavy use of UAS for Public Safety and Quality of Life may reflect the availability of low cost ($1000 USD) models used both by law enforcement and consumers. UAS for Laboratory Automation were used for delivery of samples and reagents, highlighting the emerging importance of aerial delivery.

5

Heritage Systems

As shown in Figures 4.1 and 4.2, Heritage systems are the used most frequently during a disaster, no matter the application. Heritage systems accounted for 150 out of the 203 instances (74%) and accounted from 65% to 95% of the instances in each category. The largest use of Heritage systems was for Laboratory Automation (95%), possibly reflecting the existing standards for laboratory work that does not support reactive changes and the broad base of automation systems The smallest use (65%) was Public Safety, despite Public Safety having the largest reported deployment of robots with 74 instances in total. Instead, Public Safety had the largest use of Engineering systems (31%) suggesting that the adaptability of robots was important for that work domain. As seen in Table 5.1, the use of Heritage systems was spit between UGV 73% (92 out of 119) and UAS 69% (58 out of 84).

There were 79 models of Heritage robots specifically named in the reports, too large to list; however, the large number suggest that end-users had sufficient choices for systems. 64 models of Heritage UGVs were used for 92 instances, for a ratio of 1 model to 1.4 instances. 15 models of Heritage UAS were used for 58 instances, or a ratio of 1 model for 3.9 instances. This suggests that UAS may be more general purpose, available, and more cost effective than UGV.

Table 5.1: Heritage systems by modality.

TRA	Heritage		
Modality	**UGV**	**UAS**	**TOTAL**
Total	**92**	**58**	**150**
Public Safety	15	33	48
Clinical Care	33	0	33
Continuity of Work and Education	17	3	20
Quality of Life	6	12	18
Laboratory and Supply Chain Automation	10	10	20
Non-Hospital Care	11	0	11

6

Engineering Systems

There were 27 Engineering systems instances of robots that were used for three of the six application areas (Public Safety (23), Clinical Care (3) and Continuity of Work and Education (1). Table 6.1 shows that the majority of Engineering instances (21) relied on UAS. Of the 27 instances, 18 fall in the Disinfecting of Public Spaces sub-category under the Public Safety category. Out of that 18, 17 were agricultural UAS modified to spray disinfectants, versus pesticides, in public spaces and one was a UGV with an agricultural sprayer was modified to make the sprayer more suitable for disinfecting liquids. Four instances fall in Quarantine Enforcement sub-category under the Public Safety category. Out of the four, three were UAS modified by adding loudspeakers, sirens, and flashlights and one of them was modifying an UGV by adding a camera on top of it to enforce social distancing and estimate the number of people in a park. Two instances fall under Disinfecting Point of Care sub-category under Clinical Care category, and both the instances were of modifying UGV by adding UV lights to carryout disinfection. One instance belonged to Healthcare Workers Telepresence sub-category under Clinical Care category, and the instance was modifying an UGV by fitting a screen on top of it to enable telepresence functionality. One

Table 6.1: Engineering systems by modality.

TRA	Engineering		
Modality	**UGV**	**UAS**	**TOTAL**
Total	**6**	**21**	**27**
Public Safety	3	20	23
Clinical Care	3	0	3
Continuity of Work and Education	0	1	1
Quality of Life	0	0	0
Laboratory and Supply Chain Automation	0	0	0
Non-Hospital Care	0	0	0

instance belonged to Construction sub-category under Continuity of Work, and Education category, and in this, the UAS was modified by adding lights on top of it to assist in construction post sunset. The remaining instance belonged to the Public Service Announcement sub-category under Public Safety work domain, and in this instance, a cloud based software update was released for an UGV to assist in carrying out public service announcements.

The Engineering modifications were either modifications to payloads (18), superficial morphological changes to the physical structure (8), or a new software update (1). The 18 payload modifications were to agricultural sprayers as described above. The morphological changes were to add new payloads. Three of the eight instances added loudspeakers to existing UAS (2) or a siren and flashlight to an existing UAS (1) for Public Safety. Two of the eight instances modified existing UGV (YouiBot and Turtle Bot) to carry UV-C disinfecting lights for Clinical Care. Another two instances modified an existing UGV, Spot, to either carry a camera to aid with enforcing social distancing in Public Safety or to carry a tablet to enable telepresence functionality for Clinic Care. The remaining instance was outfitting a UAS with lights to support construction of a hospital at night as part of Continuity of Work and Education. The one reported instance of a change to software was an update for the Knightscope security UGV enabling it to perform Public Service Announcements as part of Public Safety.

It is interesting to note the lack of changes to software. Software has traditionally been thought of as “soft” and easy to modify in contrast to hardware. Changing the software on an existing robot may not be possible for an end-user, as the product may not give access or the end-user does not have requisite skills, or confidence, to re-program. Hardware can be easier to modify, either the platforms support changing payloads with standardized mounts, especially prevalent on the engineered UAS, or have sufficient surfaces for fastening new payloads.

7

New Systems

There were 26 instances of New systems, as shown in Table 7.1, with the 21 of the instances innovating some aspect of UGV. All six work domains were reported to have at least one New instance. The most instances, 10, were for Clinical Care, where New innovations were for three invasive telepresence robots for sampling patients, two non-invasive telepresence robots for general patient-healthcare interaction, and five robots for support functions such as prescription/meal dispensing, enabling the patient and family to socialize, and disinfecting points of care. The second largest number of New instances was for Continuity of Work/Education (6), all for the introduction of disinfection robots into those facilities. Four New instances were reported for Quality of Life; these were distributed between Other Personal Activities (2), Attending Public Social Events (1), and Interpersonal Socializing (1). Public Safety had three New instances, all of which were for the use of thermal imaging to detect infected citizens. Two New instances appeared in Non-hospital Care, one for use of robots to allow quarantined individuals to socialize with families and the other for Off-site testing and identification of COVID in nursing homes. One New instance was reported for Laboratory and Supply Chain Automation for a novel laboratory automation robot.

Table 7.1: New Instances by novelty and modality.

Novelty	Novel Hardware/ Software			Novel Missions			Both Novel Mission and Novel Hardware/ Software		
Modality	**UGV**	**UAS**	**TOTAL**	**UGV**	**UAS**	**TOTAL**	**UGV**	**UAS**	**TOTAL**
Total	**13**	**0**	**13**	**4**	**5**	**9**	**4**	**0**	**4**
Public Safety	0	0	0	0	3	3	0	0	0
Clinical Care	7	0	7	0	0	0	3	0	3
Continuity of Work and Education	4	0	4	1	0	1	1	0	1
Quality of Life	0	0	0	3	1	4	0	0	0
Laboratory and Supply Chain Automation	1	0	1	0	0	0	0	0	0
Non-Hospital Care	1	0	1	0	1	1	0	0	0

As shown in Table 7.1, the 26 were categorized as New for one of three innovations: novel hardware or software (13), novel missions (9), or a combination both novel missions and hardware or software, i.e. completely novel (4). UGV instances (21) were far more frequent than UAS (5), and UGV instances originated from all three sources of innovation, while UAS only exhibited innovative missions.

The largest source of innovation was novel hardware or software (13 instances), all of which were UGV. Nine robots were clones duplicating existing robots or technology designed for an existing mission; the explicitly stated motivation of six of those clones was to produce a lower cost system as the existing were prohibitively expensive. A novel robot, LHF, was used in two different categories Clinical Care (2) and Non-Clinical Care (1), to provide telepresence, duplicating commercially available telepresence robots used in healthcare such as Double Robotics, Temi, Ivo, and Tommy. Similarly to LHF, a novel robot KARMI-Bot was used for telepresence in Clinical Care (1), but also for Dispensing Meals/Prescriptions (1) and Disinfection (1). Two novel robots were used in Clinical Care for Dispensing Meals/Prescriptions; these robots duplicated existing systems such as Keenon Peanut Robot and Temi. One novel robot system was developed by Amazon to disinfect warehouses and whole foods stores (Sanitation at Work/School), which appeared to duplicate commercially available UV-C disinfection robots such as UVD, Xenex, and Tru-D. Four instances of novel robots were not clones; these were built for sanitization at schools and the workplace, including two “robot” hand sanitizer dispensers constructed from Legos™.

The second large source of innovation was to meet novel missions with existing hardware or software (9 instances). Seven of the nine used existing UAS, two UGV. Quality of Life posed four novel missions generated by businesses in the service sector or by individuals. Three of these novel missions in Quality of Life used sex dolls: one instance of filling up restaurants as part of Other Personal Activities, one instance of using sex dolls with AI features in a restaurant to accompany and even make conversation with solo diners as a form of Interpersonal socializing, and Using sex dolls to fill up the soccer stadium stands for improving Attending Public Social Events. The fourth novel mission in Quality of Life was using a UAS to walk a dog, one instance in Other Personal Activities). Using thermal imagery to identify persons infected with COVID-19 accounted for four instances of use of existing robots for novel missions. Three instances addressed the novel mission Identification of Infected missions by Public Safety using unspecified UAS with thermal sensors accounted (2) and a MMC quadcopter (1). A novel mission within the Off-site Testing use cases for Non-Clinical Care was the use of an unspecified UAS to test people for COVID-19 via thermal sensing. The ninth instance of an existing robot for a new mission was the use of the AIS K9 Robot to roam around a shopping area, attracting people to come and sanitize their hands with a dispenser mounted on top (Sanitization at Work/School for the general Continuity of Work/Education work domain).

Truly new innovations, where novel robots were built for novel missions accounted for four of the 26 instances of New systems. Three robots were teleoperated throat or mouth swabbing robots for Clinical Care, specifically Healthcare Workers Telepresence. The fourth was a “robot” disinfection booth called Cleantech J1 providing Sanitation for Continuity of Work and Education. All four were UGVs.

The impact of New systems on the pandemic is unknown. In general, clones and prototypes appear to be low volume and the reports did not provide the actual adoption rate. However, reports noted that the Pinto robot developed for prescription/meal dispensing was requested by 50 hospitals in Thailand.

It is interesting to note that sanitation or disinfection was the largest objective of New systems, spanning Clinical Care (1) and Continuity of Work/Life (6). Sanitation or disinfection was tied for the largest use of Heritage systems and the largest use of Engineering systems in Clinical Care, so this suggests that, although systems existed, there was a perceived need for more systems, less expensive versions, or broad applications.

8

Discussion

As noted in the introduction, four factors are presumed to influence the adoption of robots during a disaster: *demand*, *suitability*, *availability*, and *risk*. This chapter reviews the 203 instances and concludes that these factors do appear to be influences. The review of the impact of the four influences results in a formal model of adoption of robotics during disasters.

8.1 Demand

The low number of New systems (26), and more telling, the low number of novel missions (9), novel hardware or software (13), or both (4), indicate that COVID robots adoption was driven by demand pull, not innovation push. The low number of novel missions indicates that what the end-users wanted was already established. Indeed, only five of the six work domains had one or more New systems enabling novel missions and only 40% of the use cases (12 out of 30) had an instance of a New system that involved a novel mission. The low number of instances with novel hardware or software indicates that existing robots were sufficient. While some robots used for missions were unusual, especially the quadraped Spot, and some robot modalities had not been used before for that mission, notably UAS, the opportunistic adoption of these innovations is tempered by the fact that the majority of these robots were commercially available and represented existing hardware and software being deployed for existing missions.

The distribution of New systems across the six work domains is also informative. Demand pull for existing, known missions occurred independently of work domain or use case. Furthermore, these demands, and how to meet them with robots, had already been established for 29 of the 30 use cases, as only one use (Other Personal Activities under Quality of Life) did not deploy at least one Heritage or Engineering system. Thus, there was little creation of novel robots or novel missions during COVID, consistent with other disasters

The largest demand pull for New Systems was for Clinical Care, where 21.74% (10 out of 46) of the robots were for existing missions. That Clinical Care exhibited the largest demand pull for innovation is not surprising given the role of Clinical Care in managing a pandemic. The work domain with the largest number of New systems was Quality of Life (4 or 21%), however, those New systems appeared to be split between opportunistic demand pull and innovation pull demand pull. The use of sanitation robots to maintain an individual's Quality of Life appears driven by need but also the availability of said robots. The use of consumer UAS for walking a dog and asking someone out for a date appears to be an innovation push, where the mission would not have occurred with the availability of the robots.

However, Heritage systems were not necessarily sufficient, as they did not completely meet demand pull for all existing, known missions. Consider that 15 of the use cases that deployed Heritage systems also applied at least one Engineering or New system. This suggests that Heritage systems could be improved, especially in cost.

The demand pull that resulted in Engineering or New systems was met with new payloads or physical modifications to the robot, not new or modified software. Only one instance of the 27 Engineering instances modified software and that was a minor update, while 18 changed payloads and eight modified physical morphology. There are at least three possible explanations for why hardware was modified not software:

- For most of the robots, teleoperation or shared autonomy was the primary control scheme exploiting the human as the adaptable agent and thus software did not have be changed.
- Hardware is easier to modify, while many robots use proprietary software that cannot be modified, and the population base is likely more familiar with mechanical construction (e.g., home improvement, car repair) than software.
- It is easier to project the consequences of modifying hardware as compared to the consequences of modifying software, which may introduce a hidden bug, and thus stakeholders were more willing to accept modifications.

8.2 Suitability

The same data from the previous section suggests that suitability is a major criteria in meeting demand. The large prevalence of Heritage systems and low number of New instances may mean that demand was already known, but it can also mean that only use cases for which the suitability of a robot had been established were worthy of consideration by the stakeholders. Heritage systems, by definition, have the highest congruence with the objectives of a use case and the existing work flows in that domain.

8.3 Availability

Heritage robots covered most of the use cases (29 out of 30), either directly or as the basis for Engineering, and could have covered more but were not always available in sufficient quantities or at low cost points for adoption. Robots already existed for most use cases, as seen by lack of New systems. Furthermore, 69 of models of UGV and 21 of models of UAV were reported for Heritage and Engineering, with, as reported in Chapter 5, a ratio of 1 UGV to 1.4 instances and 1 UAS for 3.9 instances. This suggests that not only were robots available, users often had a choice of robots.

However, even though robots existed, they were not necessarily available for immediate deployment at scale due to lack of inventory and costs. There were a notable number of clones (9) duplicating existing robots. Seven of these clones were for use cases in Clinical Care, most often for disinfection. The motivation reported for these clones was that existing disinfection robots were expensive and had a long wait time.

8.4 Risk

COVID-19 data confirmed the pattern of risk-adverse adoption for disasters and that this risk-adverse choices are driven by the users, not the regulations. It can be inferred that Heritage robots dominated the use cases (96.67%) and instances (73.89%) because they posed fewer risks or posed known risks. Heritage robots are low risk because, by definition, the hardware and software is mature and does not require modification (have high reliability), the use cases already exist in the sociotechnical system (have high suitability) and because the robots are already in use, the best practices are already known (have high usability).

The conclusion that adoption is risk-adverse is further supported by the fact that only three of the 203 instances clearly exposed interactants to physical danger. In these three instances, all of which were occurred within the Healthcare Workers Telepresence use case in Clinical Care, patients were exposed to increased risk because the robots were physically interacting with the person in order to take invasive samples. However, the risk of these experimental procedures was minimized via the close supervision of the operation.

While occupational and product safety regulations for robots do exist, they did not appear to be a barrier to availability or adoption. Regulations directly impacted only three instances, the aforementioned New robots for invasive samples. These robots were considered medical devices and thus had to be evaluated and approved for experimentation. The UAS were subject to each countries aviation regulations but aviation agencies generally have mechanisms for emergency use. Given that UAS were used for 84 instances in 22 countries, it seems unlikely that aviation regulations were a significant barrier. While regulations did not impact

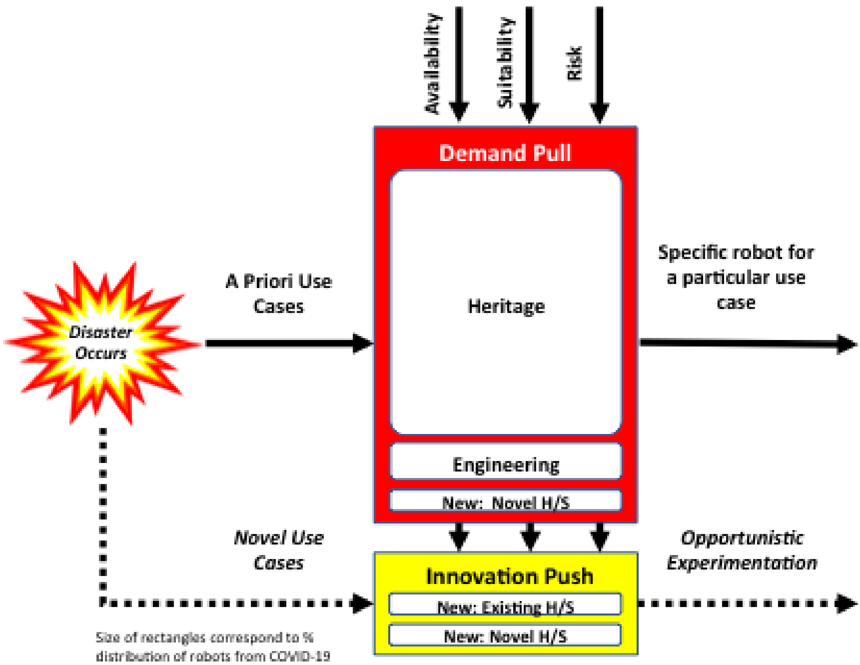

Figure 8.1: Resulting model of adoption of robotics innovation.

200 instances, of those only three New uses were considered medical devices. However, the public may have benefited from new regulations. For example, while there were seven instances from the Public Safety category where robots used thermal imaging to detect infected persons, there was no evidence that this method worked (Greenwood, n.d.) nor was the impact on the presumed infected person's privacy considered. As another example, five instances and four general discussions raised concerns of unwarranted surveillance.

8.5 Formal Model of Adoption of Robotic Innovations During a Disaster

The analysis supports a formal model of adoption of robotic innovations during a disaster shown in Figure 8.1. When a disaster occurs, stakeholders will look for robotic solutions for use cases known *a priori*, representing a demand pull. The stakeholders are likely aware of robots from peers using robots for those functions, though roboticists working in partnership with the users may be able to direct attention to applicable robots. Robots will be evaluated by the adopting stakeholder based on availability, suitability, and risk. The degree of suitability and the tolerance for performance and operational risks depends on the specific sociotechnical work domain. The evaluation appears to greatly favor the application of Heritage systems but some Heritage systems may be modified thus becoming Engineering systems, such as modifying the payload of the agricultural drone DJI MG-1P to support spraying of disinfectants. In a few cases new hardware or software has to be developed or added to meet the a priori missions, such as the cloning of UVC disinfection robots, though the novelty is again constrained by the adopting stakeholder's tolerance for risk.

However, a small number of novel use cases may emerge whereby there is no direct suitability and this provides the opportunity for valuable opportunistic experimentation. The view of robots for novel use cases as experiments is based on the following considerations. The application of robots for novel use cases broaches the potential for mismatches on suitability and introduces risks, thus they are de facto experiments. Furthermore, the robots are unlikely to be available at sufficient scale during the incident to make a notable difference in the response.

The model captures two strategies for innovating robots for novel use cases. One strategy is for stakeholders to adopt existing, available hardware or software and apply these to the novel use cases. The reliability and consequences will likely be unknown, so while the robots may be physically mature (i.e., a NASA Technical Readiness Level of 9), the readiness assessment for the use case is low (i.e., NASA TRA is New). The risk associated with the New uses requires more human oversight or accommodation to the technology, such as a fully automatic throat swabbing robot by researchers from University of Southern Denmark. This additional human oversight or accommodations effectively makes the deployment a form of in situ, opportunistic experimentation not a true operationalization of the robots into the work flow. A second strategy is for stakeholders, working with roboticists, to explore building novel platforms targeting that use case, such as the throat and mouth swabbing robots. The use of these robots is clearly a form of experimentation with much higher risk.

The model is consistent with the conservative, risk-adverse heuristics for disaster robotics from Murphy (2014) and the general UTAUT model (Venkatesh *et al.*, 2003). The model provides a post hoc explanation of the adoption decision by the Mine Safety and Health Administration (MSHA) for a novel mission of sending a robot into a collapsed mine via a narrow borehole at the Crandall Canyon Mine Disaster (Murphy, 2014). The Crandall Canyon Mine Disaster adoption decision was a notable exception to the trend from the 36 disasters, where only commercially available robots used in similar work envelopes were adopted. In the Crandall Canyon Mine Disaster, MSHA accepted an UGV constructed from commercially available components explicitly designed for creating custom pipe inspection robots, but rejected two proposed novel designed specifically for the unique application. The adopted robot was a de facto Engineering system, with lower risk than the two proposed de facto New systems, which posed higher risk because their technical maturity was low.

8.6 Limitations of the Formal Model of Adoption of Robotic Innovations During a Disaster

It should be emphasized that the model captures adoption only during a disaster, not long-term acquisition and acceptance. Adoption during a disaster may be temporary due to the ephemeral demands. The urgency of the situation may motivate institutions to waive adoption processes for the duration of the event and end-users may be willing to accept deviations in work processes that they would tolerate long-term. For example, while ground robots were used successfully at the 9/11 World Trade Center disaster, many states in the U.S.A. do not include robots on the procurement list for response teams as they are awaiting national standards to be established Murphy *et al.* (2016).

The model has at least three weaknesses. One is that the model does not show how, or when, the adopting stakeholders learn about, or begin to work with, roboticists and robots. But it does provide insight into the decision process and suggests a user-centered design process, consistent with principles of the UTAUT (Venkatesh *et al.*, 2003), where roboticists are involved with stakeholders before an event. Second, similar to the resolution of UTAUT, the model does not capture any interdependencies between suitability, availability, and risk. However, these interdependencies are pragmatic decisions where users consider, either consciously or unconsciously, trade-offs between these factors based on the practices; thus, there may be no single expression of interdependencies that holds for all work domains. Furthermore, the R4ID dataset is based primarily on social media and press reports which do not capture the reasoning behind temporary adoption decisions. Therefore, the dataset is not sufficiently detailed to analyze or predict user preferences and perception of the usefulness of robots as per Chang *et al.* (2012) and Heerink *et al.* (2010) or to capture the influences of other stakeholders (e.g., hospital, public safety department head, etc.). Follow-up research is currently being conducted to gather data to specifically identify these interdependencies and quantify the relationships for different work domains. Third, the model may reflect confirmation bias as it refines the adoption heuristic pattern for robots from one of author's previous work in Murphy (2014) and from another author's work in emergency management in Moats (2015). Concerns over confirmation bias can be explored by other researchers as the R4ID dataset is public and open for alternative analyses.

9

Conclusions

The analysis of the roboticsForInfectionDiseases.org (R4ID) dataset produces a formal model of adoption of robots, independent of modality, for disasters that can guide research development and deployment. The analysis answers the three general questions about the innovation process posed in the Introduction within the limitations of the dataset. The resulting formal model of adoption can be summarized as follows. The majority of use cases are known before the disaster or emerge from the stakeholders' understanding of their need (demand pull), not as an opportunistic reaction to robotic innovations (innovation push). Stakeholders adopt available systems with the highest technical readiness, i.e., those that maximize suitability for the use case and work flows and minimize risk. The barriers to the widespread use of robots during a disaster appear to be the lack of availability, either due to inventory or economic cost, of suitable, low-risk robots, not regulations. The dataset does not support an analysis of specific algorithms or functionality but it does lead to four recommendations for the robotics community on how to innovate for the next pandemic and for disasters in general. Current and future work is continuing to collect and analyze data, though the large size of the R4ID dataset suggests that additional data will refine the analysis but not change the trends reported in this article.

9.1 The Robotics Innovation Process During Disasters

Returning to the three questions posed in the introduction, the first question was *How do needs emerge?* The data indicates that, in general, needs emerge as a demand pull, not an innovation push, and that many high impact use cases are known before the event *a priori*. Of the 30 use cases, 29 (96.97%) were satisfied with at least one Heritage robot, which means that the needs for those cases were already known and robots in use. The impact of that use is unknown, because the reports did not capture whether a robot was limited to early adopters or early majority, but the data does show that robots which at least minimally satisfied the objectives for 29 use cases were operational prior to the pandemic.

The follow up to the first question was: *Are the use cases with the highest societal impact known a priori, are they uncovered during the incident, or emerge in some combination?* Whether these use cases had the highest societal impact, or indeed were the Heritage robots designed for societal impact versus economic viability, is also beyond the scope of this article. The number of robots, either Heritage, Engineering, or New for a use case implies impact, that stakeholders will attempt to use robots for the most pressing situations or to give themselves a benefit in accomplishing high impact tasks. Consider Public Safety and Clinical Care which comprise the two largest work domains. The impact of these robots for those work domains was not to replace workers. Indeed in seven of the 11 use cases for Public Safety and Clinical Care, the objectives were to protect the responders by allowing them to work at a distance or to delegate portions of their normative tasks (e.g., disinfection, dispensing meals or prescriptions) so that their organization could safely handle the surge in demand for their abilities. The instances of Engineering and New robots provide some insight into impact. Engineering and New robots can result from either a demand pull, i.e., that the stakeholder recognizes a need and that need is important enough to devote effort in modifying or creating a novel robotic solution, or an innovation push, i.e., that stakeholders opportunistically adopt new technology. Pubic Safety and especially Clinical Care appeared to be driven by demand pull, where even the New robots were created to help with the new demand of how to protect healthcare workers from exposure while swabbing a patient. The demand clearly originated from healthcare needs. On the other hand, the adoption of robots for Public Safety, Continuity of Work and Education, Quality of Life, and Non-Hospital Care appeared to be partially opportunistic, where the availability of commercial robots allowed the stakeholders to creatively employ the robots for New uses.

The second question was: *How robust and reliable should robots be in order to be adopted?* The high frequency of Heritage (74%) over the first four months of pandemic implies that robustness and reliability, hallmarks of those levels of technical readiness, are essential. While the high frequency might be explained by suitability and availability of Heritage systems, Public Safety, Clinical Care, and Laboratory Automation are risk-adverse work domains, supporting the role of robustness and availability. The answer to the follow up question, *is something better than nothing or robots which reproduce existing capabilities with well understood limitations more likely to be adopted*, appears to be clear. Something is not better than nothing. Consider that the largest number (10) of New systems was in Clinical Care. Those 10 instances were predominately due to clones of existing robots for disinfection because of lack of availability; the clones were so similar that they were in possible violation of intellectual property rights (Demaitre, 2020). The effort was not in developing a new robot to perform disinfection, it was in closely duplicating robots with established capabilities and work flows. Thus, the observation is that mature technologies are preferred over immature technologies.

The third question posed in the Introduction was: *What are the barriers to adoption during a disaster?* with follow on questions of *Do regulations or economic costs play notable roles? Is trust by the end-users that the robots are reliable and will perform as expected? Or is the lack of availability at scale a barrier?* Overall, regulations did not appear to be a barrier to adoption of even New robot systems. Only three of the robot instances were for use as a medical device, which would have required extensive testing. However even then, medical regulatory agencies, as well as medical insurers and institutions, have mechanisms for expedited review and waiver of regulations. Economic costs of existing robots appeared to have more of an influence, but still slight, with nine clones being built explicitly to serve as cheaper alternatives. The high percentage of Heritage (74%) and Engineering (13%) systems over four and half months could indicate that suitability, availability, and risk are the primary drivers in meeting demand pull, however, trust in the reliability and suitability as related to performance and operational risk is hard to prove from the dataset. While there is no way to estimate demand, it is reasonable to assume that given the value of robots in Clinical Care to help protect healthcare workers and cope with surge in demand for medical care and in Public Safety for preventing and diagnosing infections, robots probably could have been used more frequently and thus with greater impact if there were more robots available. Thus availability of suitable, low risk robots, i.e., those already in use (Heritage) or having ability to be safely adapted (Engineering), is the most significant barrier.

Although the R4ID dataset shows that the large majority (87%) of use cases relied on existing robots, this does not mean existing robots were optimally suitable for the pandemic, only that they were sufficiently suitable, low-risk, and available to be adopted by generally conservative stakeholders. The types of reports in the R4ID database generally do not describe gaps or problems with the technology as they tend to be written as positive press announcements. Thus the dataset is not directly useful as a tool for documenting the need for specific robotic technologies, such as manipulation and increased autonomy, but does identify fundamental research topics.

9.2 A Formal Model of Diffusion of Robotic Innovation During Disasters

The data supports the model of diffusion of robotic innovation during disasters given in Figure 8.1 and suggests that the findings will apply to all disasters. As predicted, existing systems with high technical maturity are either used in greater numbers or adapted to meet demand pull, while truly novel systems are rare and reflect the opportunity for field experimentation.

Consider that for the first four and a half months of the COVID-19 pandemic in 34 countries, the large majority of robot systems had high technical maturity. The mechanical and software maturity was high by TRL standards, given that 69 UGV and 21 UAS existing were commercially available and thus were TRL 9. More importantly, the TRA was high; out of the 203 instances, 15 (74%) were Heritage and 27 (13%) were Engineering while only 26 (13%) were New. Even with the extended time of the pandemic as compared with the short response times of a wildfire or flash flood, adoption favored existing robots and when those were not available, some stakeholders created unauthorized clones of those robots.

The model is expected to apply to all hazards because the pattern of adoption was the same for six very diverse sociotechnical work domains. The data indicates that adoption in all six sociotechnical work domains appeared to be driven by demand pull and the availability of existing or easily engineered systems to meet demand. While there was no direct discussion of risk in the reports, the deployed systems appeared to minimize risk of physical harm and risk of unintended consequences because they showed high reliability, usability, and suitability.

9.3 Recommendations for the Robotics Community

While the dataset does not support the analysis of gaps in specific functionality, the formal model of adoption highlights four barriers which can guide robot research for disasters. As shown in Figure 9.1, the inputs to the adoption process reflect opportunities to acceleration adoption.

1. *Identifying the a priori use cases and understanding the constraints of the sociotechnical work domain that impact novel use cases before the disaster.* The model suggests that prior to, and worst case during, a disaster, the focus should be on working directly with users to determine their needs (demand pull) and meet those needs with low risk systems rather than try to find ways to

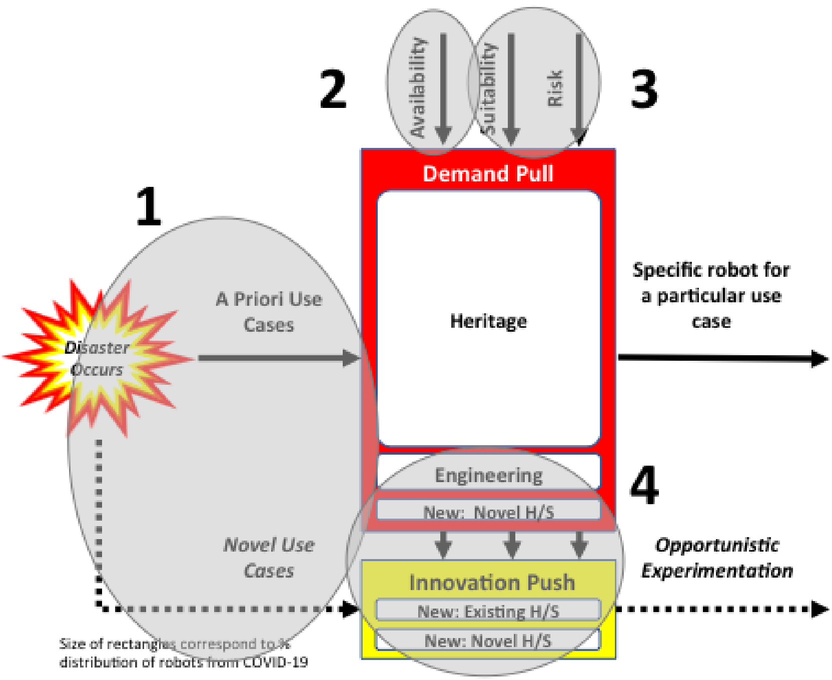

Figure 9.1: Four barriers to adoption implied by the model of adoption of robotics innovation.

insert their research (innovation push). The adoption process is primarily driven by demand pull, so it is critical to understand what the users want, or think they want, and to work with them. Adoption is also influenced by understanding the work domain in order to minimize risk of unintended consequences, ranging from unreliable operation (performance risk) to increased demand manpower (operational risk). Understanding the work domain is also essential for successfully innovating Engineering or New platforms. *The model suggests that i) roboticists adopt a user-centered research paradigm and ii) fundamental research is needed on methods to predicting reliable use and on projecting increasing in workload on the enterprise and cognitive workload on individual users.*

2. *Creating new design and distribution mechanisms for the rapid manufacture of reliable, easily adaptable robots to increase availability.* The model shows that availability of trustworthy robots is a key component to adoption. However, availability during a disaster is challenging because the response poses a rapid, sudden surge in demand that may exceed existing inventory or the budgets of adopting agencies. Therefore, a robotics infrastructure is needed to meet on demand production capacity, providing the ability to rapid produce and distribute low risk robots. Rather than rely on caches of robots, which can become outdated, an alternative strategy is to focus on general purpose designs that optimize rapid manufacture and high usability (see Murphy *et al.*, 2020). Note, robotics for disasters should not be viewed just as a manufacturing or open source problem, because such systems must be suitable for the work domain during the disaster, most notably support ease of use due to the lack of time to train. The creation of a robotics infrastructure introduces a related major challenge: *How to evaluate designs and the correction operation of any updates in hardware, software, and user experience in the absence of actual disasters.*

3. *Creating formal methods to predict suitability and risk of robots for work envelopes, complex sociotechnical work flows, and new*

use cases. The model indicates a strong preference for Heritage systems (150 out of 203), which by definition have established suitability and known risks. Indeed nine out of 26 New systems were clones, rather than truly novel robots. While the data does not capture how many more hospitals, agencies, companies, and individuals could have adopted robots, the model, and prior empirical evidence in Murphy (2014), suggests that their willingness to adopt will be based on their comfort level that the robots will not make matters worse. Currently robotics can only offer subjective assurances or performance data on specific functions, e.g., NIST Rescue Robot course (Jacoff *et al.*, 2001). Therefore, *fundamental research is needed to create methods that can rapidly assess i) the viability of a robot for a novel work envelope and ii) its impact on the organization's work flows.* In order to predict the risk of failure for new work envelopes, fundamental research in how to represent work envelopes that capture distinctions between working in a hospital intensive care unit with glass walls and in a large warehouse with narrow aisles.

4. *Creating general purpose robots that can be easily, and safely, modified.* In order to increase the rapid development and safe use of Engineering and New systems during a disaster, fundamental research and development is needed in creating general-purpose robots capable of accepting plug-and-play payloads, supporting physical modification, and enabling shared autonomy. Research is also needed in projecting the risk incurred by such modifications. Engineering systems accounted for 27 instances, and the majority (18) used general-purpose UGV or UAS designed to safely accept different payloads. In terms of shared autonomy, the UAS provide teleoperation as a default mode of interaction, allowing the human to adapt it to new uses; while this increases the cognitive workload of the operator, it does provide flexibility. The UAS, especially those by DJI, also permit third party software, which increases shared autonomy functionality. In contrast, UGV tended to be specialized for specific uses, with autonomy either basic teleoperation without guarded motion or full autonomy, and thus less adaptable.

> Robotics might have a bigger impact on pandemics, and disaster response in general, if there are more general-purpose robots with plug-and-play payloads, have the ability to be physically modified, and provide open developer kits. However, as noted in the previous barrier, the general purpose systems must be low risk as well as available.

The findings suggest research and development of robots for future disasters should focus on five goals: designing robots to meet pre-existing demands, integrating robots into operational use prior to the disaster, creating robots or software that support multiple uses, developing formal methods for projecting the risk of using the robot in terms of direct and indirect performance and consequences, and increasing the availability and functionality of Heritage robots by reducing cost and increasing on demand manufacture. The use cases for robots for pandemics are mostly known, given that 29 of the 30 use cases employed Heritage systems. What is missing are robots which are more affordable, and thus more likely to be available, and easily manufactured, thus increasing availability upon demand. The data suggests that the priority is to design and operationalize robots for routine use, as the robots already in use are the ones that are used during a disaster. The data also suggests that the robots have to have a clear cost/benefit ratio and be reasonably priced; this may require advances in manufacturing. The findings also highlight the need for general purpose, easily adapted robots where a robot routinely used for *Use A* can be physically modified and directed for *Use B*. Such robots would also improve the cost/benefit ratio. However, good robot design may not be enough. While regulations did not appear to be a barrier to adoption, policy may be. Consider that for Clinical Care, Laboratory Automation, and Non-clinical Care uses, the adoption of robots depends on how insurers cover new technology and government incentives, both of which are beyond the purview of roboticists.

9.4 Current and Future Work

Additional work analyzing the adoption of robots for disasters, especially the role of technical maturity over time and by country is in progress. Data is continuing to be collected and scientific publications are beginning to emerge which will better document uses and impact, especially during the first few months and for applications that may not have been deemed worthy of press releases or posting on social media. These reports may retroactively change the specifics of the distribution of use cases and the technical maturity rankings, but given the large number of 203 existing instances, these new reports are likely to refine and sharpen findings, not radically change them. Current work is following up on key work domains, especially Clinical Care, to determine any technical barriers or need for improvements (e.g., needed software to autonomously perform function F). Also follow up interviews with end-users are being conducted to determine the relative weighting of factors on their adoption decisions during the pandemic and how it differed from normative adoption processes. As the model is restricted to the exceptional adoption processes during a disaster, the model is unlikely to accurately predict long-term adoption. The R4ID dataset is available at roboticsForInfectiousDiseases.org to allow other researchers to add new instances and to conduct their own analyses.

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