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# Context-Enabled Visualization Strategies for Automation Enabled Human-in-the-loop Inspection Systems to Enhance the Situation Awareness of Windstorm Risk Engineers

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CONTEXT-ENABLED VISUALIZATION STRATEGIES FOR AUTOMATION ENABLED  
HUMAN-IN-THE-LOOP INSPECTION SYSTEMS TO ENHANCE THE SITUATION  
AWARENESS OF WINDSTORM RISK ENGINEERS

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A Dissertation  
Presented to  
the Graduate School of  
Clemson University

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In Partial Fulfillment  
of the Requirements for the Degree  
Doctor of Philosophy  
Civil Engineering

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by  
Sruthy Orozhiyathumana Agnisarman  
December 2019

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Accepted by:  
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Dr. Kalyan Piratla  
Dr. Patrick Rosopa

## ABSTRACT

Insurance loss prevention survey, specifically windstorm risk inspection survey is the process of investigating potential damages associated with a building or structure in the event of an extreme weather condition such as a hurricane or tornado. Traditionally, the risk inspection process is highly subjective and depends on the skills of the engineer performing it. This dissertation investigates the sensemaking process of risk engineers while performing risk inspection with special focus on various factors influencing it. This research then investigates how context-based visualizations strategies enhance the situation awareness and performance of windstorm risk engineers.

An initial study investigated the sensemaking process and situation awareness requirements of the windstorm risk engineers. The data frame theory of sensemaking was used as the framework to carry out this study. Ten windstorm risk engineers were interviewed, and the data collected were analyzed following an inductive thematic approach. The themes emerged from the data explained the sensemaking process of risk engineers, the process of making sense of contradicting information, importance of their experience level, internal and external biases influencing the inspection process, difficulty developing mental models, and potential technology interventions. More recently human in the loop systems such as drones have been used to improve the efficiency of windstorm risk inspection. This study provides recommendations to guide the design of such systems to support the sensemaking process and situation awareness of windstorm visual risk inspection.

The second study investigated the effect of context-based visualization strategies to enhance the situation awareness of the windstorm risk engineers. More specifically, the study investigated how different types of information contribute towards the three levels of situation awareness. Following a between subjects study design 65 civil/construction engineering students completed this study. A checklist based and predictive display based decision aids were tested and found to be effective in supporting the situation awareness requirements as well as performance of windstorm risk engineers. However, the predictive display only helped with certain tasks like understanding the interaction among different components on the rooftop. For remaining tasks, checklist alone was sufficient. Moreover, the decision aids did not place any additional cognitive demand on the participants. This study helped us understand the advantages and disadvantages of the decision aids tested.

The final study evaluated the transfer of training effect of the checklist and predictive display based decision aids. After one week of the previous study, participants completed a follow-up study without any decision aids. The performance and situation awareness of participants in the checklist and predictive display group did not change significantly from first trial to second trial. However, the performance and situation awareness of participants in the control condition improved significantly in the second trial. They attributed this to their exposure to SAGAT questionnaire in the first study. They knew what issues to look for and what tasks need to be completed in the simulation. The confounding effect of SAGAT questionnaires needs to be studied in future research efforts.

## DEDICATION

This work is dedicated to my parents, O. A. Agnisarman and Savithri Antherjanam for their unconditional love and my beloved husband Praveen Nedumpully Govindan for his support.

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## CHAPTER ONE

### INTRODUCTION

Infrastructure inspection is the evaluation of the physical and functional conditions of civil infrastructure systems such as buildings, highways, bridges and sewer/water pipelines (Fenves, 1984). This is primarily a visual inspection process involving inspection personnel or team going to the inspection site to assess the condition of civil infrastructure. The objective of this process is the detection of any visual changes, such as leakages, cracks and corrosion, in these structures over the course of time (Stent, Gherardi, Stenger, Soga, & Cipolla, 2016). Civil infrastructure systems such as buildings, highways, bridges and tunnels need to be inspected routinely to prevent its failure. Condition assessment as well as the prediction of future state of the infrastructure must be implemented into the infrastructure maintenance plan (Ariaratnam, El-Assaly, & Yang, 2001). Traditional infrastructure inspection process involves inspectors physically going to the site, which can be time consuming and expensive (Lattanzi David & Miller Gregory, 2017). In addition, traditional risk inspection involves collecting primarily qualitative information, rendering it highly subjective. Without relevant quantitative information collected by the inspectors, the qualitative data provide only limited information and may be seen as irrelevant (Ellenberg, Kotsos, Moon, & Bartoli, 2016; Khan et al., 2015).

To improve the effectiveness of infrastructure, various advanced technologies have been widely adopted (Zucchi, 2015.). The advantages of such systems include its ability to host a variety of intelligent sensing systems, real-time data analysis capability and its ability to collect data remotely with minimum task disruption and risk (Almadhoun, Taha,

& Seneviratne, 2016; Gucunski et al., 2015; Lattanzi David & Miller Gregory, 2017). A variety of sensing systems including lidar, sonar, RGB camera and radar have been used to collect both qualitative as well as quantitative data (Agrawal et al., 2008; Ékes, 2016; Ékes Csaba, Neduczai Boriszlav, & Henrich Gordon R., 2011; Eschmann, Kuo, Kuo, & Boller, 2012). Computer vision techniques and algorithms such as target detection and edge detection algorithms are used on the data collected by these techniques to facilitate inspector's decision making by improving the accuracy of the inspection process (Chae & Abraham, 2001; Ellenberg et al., 2016; Torok, Golparvar-Fard, & Kochersberger, 2013). In addition, navigation and path planning algorithms reduce the risk to the engineers by minimizing their exposure to adverse site conditions (Gucunski et al., 2015; Lim, La, & Sheng, 2014).

## **PROBLEM STATEMENT**

As technology advances, users have access to copious amount of information. However, managing and making sense of this information can be a challenging task (Riveiro, Falkman, & Ziemke, 2008). Although these technologies facilitate decision making, manual inspection is still the fundamental step in assessing civil infrastructure (Zhu, 2011). Further, the performance of the operator depends on various factors such as degradation of situation awareness (SA), automation complacency and vigilance decrement (Endsley, 1999; Endsley & Kiris, 1995). Automation complacency often leads to out-of-the-loop performance problems (Endsley & Kiris, 1995). Although these issues have been investigated in detail in visual inspection in other domains such as aircraft maintenance and manufacturing, there have been only limited research focusing on the

importance of these issues in the domain of civil infrastructure inspection. Since the skill sets of individuals performing civil infrastructure inspection is quite different from the personnel in the other domains, there is a need to conduct more research focusing on the needs of people performing civil infrastructure inspection. Further, SA has been primarily investigated in the context of dynamic environment where the situation changes rapidly. Though infrastructure inspection process doesn't involve any dynamic scenarios, SA is equally important in this context as well. So, this SA requirement also demands special attention from human factors researchers.

This lack of research in this domain prompted us to look for studies in the domain of aircraft inspection and maintenance. One of the seminal papers about the SA requirements in the context of aircraft maintenance explains how three different levels of SA manifest during aircraft inspection and maintenance task (Endsley & Robertson, 2000). Level 1 SA in this scenario includes the detection of various defects such as metal fatigue, fluid leaks and wear. Level 2 SA is the inspector's comprehension of these defects or elements they observed in the first level. Level 2 SA is a diagnostic step involving the inspector detecting the reasons for these issues. While attaining Level 2 SA from Level 1 SA, the data gathered are processed and synthesized. According to (Endsley, 2015), this process is sensemaking, or making sense of the information available, which is a deliberate process in this context. Finally, Level 3 SA involves the projection of these issues on the performance of aircraft in the future (Endsley & Robertson, 2000). As Endsley and Robertson (2000) explained, the concept of SA is generally applied in dynamic systems.

However, inspection of complex systems such as aircrafts and civil infrastructure can also be challenging.

Similar to aircraft maintenance scenario, civil infrastructure inspection also involves the prediction of the performance of the system in the future or in the event of extreme weather condition. This requires the inspection engineer to attain the highest level (Level 3) of SA. Endsley and Robertson (2000) explains how reaching Level 3 SA can be challenging for aircraft maintenance personnel as they don't receive any feedback on the effects of their action. This is true in the context of infrastructure inspection as well. The inspection personnel will hardly receive feedback on the accuracy of their prediction. This inherent nature of such inspections makes the process of achieving Level 3 SA a challenging task.

This skill to project the state of the infrastructure to future is especially important in insurance risk inspection, which is a specific type of infrastructure inspection. Insurance risk inspection, also termed as loss prevention surveys are carried out to ensure the safety and stability of the structure by reducing the severity of losses (Schlesinger & Venezian, 1986). Insurance companies provide different types of loss-prevention services such as fire protection, windstorm and earthquake surveys for infrastructure insurance based on the type of insurance policy. Windstorm inspection is a type of visual risk assessment survey performed to investigate and identify the risk factors that might result in severe damages in the event of extreme weather conditions such as hurricanes or tornados ("What is the Windstorm Inspection Program?," 1999). Like general infrastructure inspection, windstorm loss prevention surveys also involve a risk engineers going to the site to assess

various risk factors associated with that particular infrastructure. Predicting the future state of the infrastructure is a crucial step in loss prevention survey, because the only time they can check the accuracy of their report is when they do a post-catastrophic loss investigation process. Past research have shown that predicting and forecasting into future can be a challenging task even for experts. People are often overconfident in their own predictions (Pugh, Wickens, Herdener, Clegg, & Smith, 2018). This uncertainty in future prediction is a result of lack of knowledge on the chance of events to occur, which in turn makes it probabilistic (Lipshitz & Strauss, 1997; Pugh et al., 2018). Even with the application of automation enabled technologies and intelligent sensors, this gap may not be bridged as the engineers are still required to make sense of the information gathered by such intelligent systems.

### *Purpose of the Study*

One potential way to improve the Level 3 SA of risk engineers is by developing visualization strategies and decision aids facilitating their decision making. As Riveiro et al. (2008) explained, fusing information from multiple sources to understand the interaction among various elements and presenting it in an interactive way would support the situation awareness of the users. Such visualization strategies aiding risk engineers to predict the future state of the infrastructure system need to be developed. However, to develop such systems, there is a need to understand the sensemaking process and specific needs of risk engineers. The primary objective of this dissertation project is to investigate the effectiveness of various visualization strategies to improve the SA of infrastructure inspectors, specifically windstorm risk engineers.

## **THEORETICAL FRAMEWORK**

This study is based on the SA theory proposed by Endsley, (1995b). According to this theory SA is a construct achieved through situation assessment. It involves three levels: Level 1 involves perceiving elements/cues in the environment. Level 2 involves comprehending these elements and Level 3 involves projecting the status of the elements to the future. This concept is studied in detail in other domains such as aviation and aircraft maintenance. We try to draw parallels with these domains to understand the SA requirements of infrastructure inspection engineers. As the first step, we used the data/frame theory of sensemaking proposed by Klein, Phillips, Rall, & Peluso (2007) to understand how infrastructure inspectors make sense of the information available in the environment. Data/frame theory of sensemaking suggests that this process is a closed-loop transition between mental model formation and mental simulation. The sensemaking process begins with seeking information to find an anchor to establish a useful frame (a structure accounting for the data). This frame/hypothesis/mental model provides shape to the data. Then more data will be collected to elaborate the frame. The frame will then either be questioned or updated based on the data collected. If the new information contradicts the existing frame, the frame will be questioned and if it is consistent with the existing frame, the frame will be elaborated. If the inspector is satisfied with the current frame, that frame will be preserved. One of the results of questioning an existing frame is reframing. While going through reframing process, up to three frames may be tracked (Gary Klein et al., 2007). Alternative frames are considered to identify a frame that best fits the data.

## RESEARCH OBJECTIVES

The primary objectives of this dissertation project is to investigate the effectiveness of various visualization strategies to improve the SA of infrastructure inspectors, specifically windstorm risk engineers. More specifically, this dissertation explores the following research problems:

1. Understanding and characterizing various automation enabled infrastructure inspection techniques focusing in the human factors considerations of using such techniques.
  - a. To understand the state of the art of automation assisted infrastructure inspection systems
  - b. To explore the limitations of automation assisted infrastructure inspection systems
  - c. To understand the extent of integration of human factors principles in the design and integration of automation assisted infrastructure inspection
2. Investigating the sensemaking process of risk engineers while performing risk inspection using the data/frame theory of sensemaking, proposed by (Gary Klein et al., 2007), through a qualitative research approach.
  - a. To understand the needs of windstorm risk engineers
  - b. To investigate potential strategies to improve the SA of risk engineers
3. Investigating the effectiveness of various visualization aids to improve the SA of infrastructure inspectors, more specifically risk engineers.

4. Investigating the transfer or training effect of the visualization aids used to improve the SA of risk engineers.

### *Research Questions*

The overall research questions are listed below:

1. What is the status of the research in the domain of automation assisted infrastructure inspection process?
2. What process do windstorm risk engineers employ to make sense of the information available to them?
3. What is the extent to which the theory of SA (Endsley, 1995) is applicable in the domain of infrastructure risk inspection?

## **DISSERTATION ORGANIZATION**

This dissertation is organized as follows: Chapter 2 details the results of the systematic review of literature on automation enabled infrastructure inspection systems. Chapter 3 discusses the results of the qualitative research to understand the sensemaking process of risk engineers within the framework of data/frame theory of sensemaking. Chapter 4 explores the effectiveness of these context-based visual decision aids. Chapter 5 explores the transfer of training effect of these decision aids. Chapter 6 summarizes the findings and discusses future research directions.



## CHAPTER TWO

### A SURVEY OF AUTOMATION-ENABLED HUMAN-IN-THE-LOOP SYSTEMS FOR INFRASTRUCTURE VISUAL INSPECTION

#### **INTRODUCTION**

Infrastructure inspection is the evaluation of the physical and functional conditions of civil infrastructure systems such as buildings, highways, bridges and sewer/water pipelines (Fenves, 1984). This process, which is primarily vision-based, involves detection of any visual changes, such as leakages, cracks and corrosion, in these structures over the course of time (Stent et al., 2016). A trained inspector visits the site and assesses their condition by looking over the structure and recording the qualitative aspects of the infrastructure (Kuo et al., 2016). Infrastructure systems such as road networks, bridges, tunnels, pipelines and dams require inspection on a regular basis (Lattanzi David & Miller Gregory, 2017) to detect defects prior to their development into failures. The current inspection processes are often time-consuming, requiring the interruption of the regular functioning of the infrastructure system. As a result, the standard procedures used are limited in terms of the time and access requirements. These issues, especially the latter, result in delays in the inspection process, leading to longer gaps between inspections (Henrickson, Rogers, Lu, Valasek, & Shi, 2016). In addition, the conventional inspection processes are expensive. More importantly, these inspections require a team of experienced professionals operating complex systems possibly risking their lives under hazardous working conditions (Ellenberg et al., 2016; Henrickson et al., 2016; Lattanzi David & Miller Gregory, 2017). For example, highway or bridge infrastructure inspection requires

lane closures and direct exposure of inspectors to highway traffic (Lattanzi David & Miller Gregory, 2017). In addition, the inspection process is often subjective with the accuracy of the findings depending on the inspector's skills and experience. Without relevant quantitative information collected by the inspectors, the qualitative data provide only limited information and may be seen as irrelevant (Ellenberg et al., 2016; Khan et al., 2015). These challenges highlight the inefficiency and the cost of the current conventional inspection methods.

Conventional infrastructure inspection is conducted by a skilled inspector who physically goes to the site and performs the inspection task (Lattanzi David & Miller Gregory, 2017). With the advancement of computing and information technology, the application of such automated technologies as unmanned aerial vehicles has increased over the past few years (Zucchi, 2015.), with these systems being widely used today for infrastructure inspection to complete the task with minimum disruption and risk at reduced cost (Lattanzi & Miller, 2017). Unlike human inspectors, such technologies are consistent (Newman & Jain, 1995), and Unmanned Aerial Vehicles (UAVs) such as drones and helicopters can extend the capabilities of human operators, augmenting their accessibility to structures. In addition, because these systems could be equipped with laser technologies, Global Positioning System (GPS) systems, cameras, and thermal imaging techniques for navigation and data collection (Gucunski et al., 2015), they are capable of collecting both quantitative data such as dimensions, moisture content and material properties and qualitative information such as the physical appearance and general condition (Agrawal et al., 2008; Ékes, 2016; Ékes Csaba et al., 2011; Eschmann et al., 2012). This ability to

collect quantitative as well as qualitative information facilitates informed decision making pertaining to infrastructure management (Lattanzi & Miller, 2017).

One of the most promising features of these automaton-assisted inspection systems is their intelligent sensing capability using non-destructive technologies. The use of such sensors improves the quality of the data collected as well as provides real-time data analysis capabilities (Almadhoun et al., 2016; Gucunski et al., 2015). Moreover, algorithms have been developed to improve the efficiency of the inspection process by making the system autonomous, thereby reducing human involvement. For example, target detection algorithms can detect damages such as cracks, rust or spalling from the imagery collected using high resolution cameras integrated in the inspection system, thereby improving the efficiency and accuracy of the inspection process by reducing the subjectivity of human inspectors (Chae & Abraham., 2001; Ellenberg et al., 2016; Torok et al., 2013). In addition, autonomous operation of robotic systems facilitated by a path planning algorithm reduces the risk to the inspector (Gucunski et al., 2015; Lim et al., 2014) and minimizes the time required to complete the inspection process (Lattanzi & Miller, 2017).

Data collection using automated systems reduces the risk to the inspectors by eliminating the need for them to go physically to a dangerous inspection environment. For example, implementation of remotely operated autonomous systems for bridge inspection reduces the exposure of inspectors to traffic (Gucunski et al., 2015). Commercially available UAVs used for such infrastructure inspection are inexpensive and can be equipped with other inexpensive hardware units for sensing, data processing and navigation (Máthé & Buşoniu, 2015). These systems, which are primarily used for vision-

based inspection, eliminate the need for disrupting the normal operation of the infrastructure system (Khan et al., 2015). Though the advantages of unmanned aerial systems are promising, these systems are significantly affected by disturbances in the external environment (Lattanzi & Miller, 2017). Moreover, the inspector has to be skilled at controlling these complex robotic systems. Though automation assisted technologies can assist inspectors while performing inspection and maintenance tasks, such tasks are not 100% automated yet. None of the articles reviewed in this paper investigated the use of a fully automated system.

Operator performance in an automation enabled system is mediated by vigilance decrements, complacency and loss of situation awareness (SA), which have been discussed at length in the literature (Endsley, 1999; Endsley & Kiris, 1995). In addition, studies suggest that the SA of the operators may be degraded because the automation will accomplish some of the tasks with minimal operator intervention (Cummings, 2004). SA is the perception of the elements/cues in the environment (level 1), comprehension of the current situation of the elements (level 2) and the projection of the status of the elements and environment in the future (level 3) (Endsley, 1995b). Any of these levels of SA can be affected by automated systems that keep humans out-of-the-loop. Going out-of-the loop is a known consequence of automation as explained in the earlier studies on human-automation interaction (Endsley & Kiris, 1995). Out of the loop performance problems are characterized by a decreased ability of the human operator to intervene in system control loops and assume manual control when needed in overseeing automated systems. First, human operators acting as monitors have problems in detecting system errors and

performing tasks manually in the event of automation failures. Hence, it is important to keep the operator in the loop to avoid potential automation failure. In addition, making sense of the data generated by such technologies can be challenging. In order to further the research pertaining to the application of automated technologies in infrastructure inspection, it is important to understand the state of the art and the limitations associated with such technologies. The diversity of the application domain and the number of research studies published investigating various visual inspection technologies render it difficult for researchers and practitioners to comprehend the advantages and disadvantages of such technologies.

Accordingly, the systematic review reported here aims to investigate the application of automated systems for infrastructure assessment following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) format. To explore the recent developments in this domain, we reviewed peer-reviewed journal and conference articles published from 2000 to 2018. Our specific objectives were to 1) determine the primary application domains of automation-assisted visual inspection, 2) to identify the types of sensing technologies used for automated infrastructure inspection, 3) to classify the articles identified here based on the extent of the involvement of the machine in conducting the inspection tasks, 4) to determine the types of navigational and control technologies used, 5) to identify the types of algorithms used for navigational purposes and data processing and analyses, and finally 6) to identify the gap in the literature and propose future research directions.

## METHOD

### *Inclusion and exclusion criteria*

This study included research articles involving automation enabled infrastructure visual inspection technologies, published in peer-reviewed publications and conference proceedings in English after 2000. Studies not involving visual inspection technologies were excluded. Furthermore, review papers, posters, extended abstracts or patented technologies were not included in this study.

### *Search strategy and outcomes*

This research was exempted from approval by the Clemson University Institutional Review Board, because no active subjects participated. A broad search for articles in English published since 2000 was conducted using Web of Knowledge, ASCE Library, ACM Digital Library, and IEEE during the months of July and August 2017 and July 2018. A combination of keywords listed in Table 2.1, connected using Boolean operators (and/or), yielded 1048 articles. First, these articles were screened based on title and abstract for the following exclusion criteria: review papers, conference proceedings, letters, comments or extended abstracts, articles not exploring visual inspection and languages other than English, resulting in 865 being excluded. The 183 remaining articles were subsequently screened based on their full texts; 137 of these 183 articles were found not to satisfy the inclusion criteria and were, therefore, excluded. In addition, 15 articles cited by the articles selected were also screened, with 7 of them satisfying the inclusion criteria. At the end of the screening process, a total of 53 articles were selected for this review. Figure 2.1 shows the literature selection process.

Table 2.1. Keywords used

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Infrastructure	Risk
Inspection	Robots
Automation	UAV
Sensors	Drone
Insurance	

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*Data abstraction and synthesis*

Selected articles were reviewed thoroughly, and data were extracted to systematically synthesize the information pertinent to the scope of this review. The extracted details are categorized and summarized in Appendix A, with the Results Section providing more detailed information about the individual categories. Table 2.2 lists the journals and conference proceedings in which the articles reviewed were published.

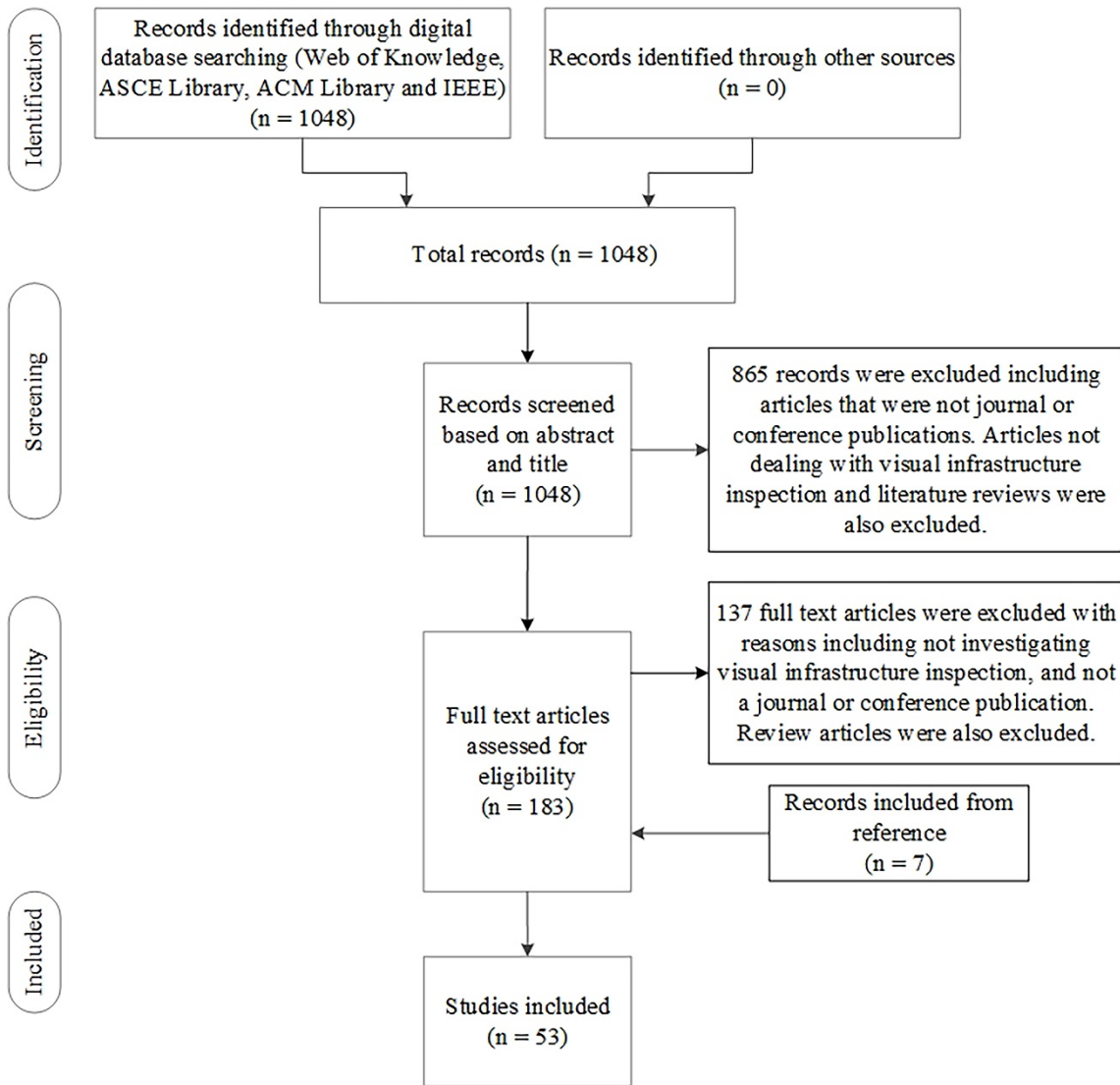


Figure 2.1. Article selection process



Table 2.2. Journals and conference proceedings in which the selected articles were published

Area	Journal	Conference
Civil Engineering	Journal of Computing in Civil Engineering (ASCE)	Pipelines Conference (ASCE), Structures Congress (ASCE),
	Journal of Performance of Constructed Facilities (ASCE)	International Conference on Computing in Civil and Building Engineering (ASCE)
	Journal of Infrastructure Systems (ASCE)	Construction Research Congress (ASCE)
	Journal of Performance of Constructed Facilities (ASCE)	International Conference on Rail Transportation (ASCE)
	Journal of Survey Engineering (ASCE)	European Workshop on Structural Health Monitoring
	Journal of Performance of Constructed Facilities (ASCE)	Smart Structures and Material Systems + Nondestructive Evaluation and Health Monitoring (SPIE)
	Automation in Construction (Elsevier)	Health Monitoring of Structural and Biological Systems (SPIE)
	Structural Control and Health Monitoring (Wiley Online Library)	
Nuclear Engineering	Nuclear Engineering and Design (Elsevier)	
	Journal of Nuclear Science and Technology (Taylor & Francis Online)	
Electrical Engineering	Journal of Field Robotics (Wiley Online Library)	International Conference on Advanced Robotics (IEEE)
		International Conference on Unmanned Aircraft Systems (IEEE), International Conference on Field and Service Robotics (Springer)
Petroleum Engineering		Saudi Arabia Section Annual Technical Symposium and Exhibition (Society of Petroleum Engineers)
		Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS)
Remote Sensing and Computer Vision	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences	Remote Sensing and Spatial Information Sciences (ISPRS)
	Remote Sensing (MDPI)	The International Conference on Quality Control by Artificial Vision (SPIE)
System/Mechanical/ Electronics/Industrial Engineering	Transactions on Mechatronics (IEEE/ASME)	International Mechanical Engineering Congress and Exposition (ASME)
	Transactions on Automation Science and Engineering (IEEE)	Systems Conference (IEEE)
	Smart Materials and Structures (IOP Science)	International Conference on Intelligent Robots and Systems (IEEE)
	Robotics and Computer-Integrated Manufacturing (Elsevier)	
	IEEE Systems Journal (IEEE)	
Ocean Engineering	Ocean Engineering (Elsevier)	Oceans (IEEE)

## RESULTS

The primary themes identified from the data synthesis were the type of automation used, the levels of automation, the sensors/technologies used for data collection and navigation, the control mechanism and the algorithm used for data analysis as detailed in Appendix A. Of the 53 studies reviewed in this research, 26 were conducted in the United States; six in Canada; three each in Korea, and Spain; two each in Australia, China, Germany, Italy, and Japan; and one each in Brazil, France, Greece, Italy, Scotland, and the United Arab Emirates, with three studies involving collaboration of researchers from more than one country.

### *Application domain*

The application of automation-assisted inspection can be seen in a wide variety of domains ranging from bridge inspection to ship hull and harbor inspection, with bridge inspection being the most frequently addressed domain (20 studies). Other applications include pipeline inspection (9 studies), road inspection (4 studies), building inspection (3 studies), tunnel/culvert inspection (3 studies), power line/cable inspection (2 studies), nuclear power plant and reactor vessel (2 studies), dam inspection (2 studies), masonry wall inspection (1 studies), oil and gas refinery (1 study), harbor and ship inspection (1 study), and underwater application (1 study). Two studies investigated the application of autonomous system for general infrastructure inspection (Romulo Gonçalves Lins, Givigi, Freitas, & Beaulieu, 2018; Rea & Ottaviano, 2018).

More specifically, 20 of the 53 studies explored the possibility of automating bridge inspection (Chen, Rice, Boyle, & Hauser, 2011; Ellenberg, Branco, Krick, Bartoli, &

Kontsos, 2014; Ellenberg, Kontsos, & Moon, 2016; Ellenberg et al., 2016; Eschmann Christian & Wundsam Timo, 2017; Gucunski et al., 2015; Hackl, Adey, Woźniak, & Schümperlin, 2017; Harris, Brooks, & Ahlborn, 2016; Hiasa, Karaaslan, Shattenkirk, Mildner, & Catbas, 2018; Khaloo, Lattanzi, Cunningham, Dell’Andrea, & Riley, 2018; Khan et al., 2015; La et al., 2013a, 2013b; Lim et al., 2014; Lins & Givigi, 2016; Moselhi, Ahmed, & Bhowmick, 2017; Murphy et al., 2011; Son, Hwang, Kim, & Kim, 2014; Wang et al., 2017; Yoder & Scherer, 2016), and four articles investigated the application of automation assisted technologies for highway inspection (Fujita, Shimada, & Ichihara, 2017; Villarino, Riveiro, Martínez-Sánchez, & Gonzalez-Aguilera, 2014; Wang & Birken, 2015, Yeum, Choi, & Dyke, 2017). These statistics reflect the importance of the timely maintenance and repair of bridge structures and highways, for they are among the most critical infrastructures supporting our communities. Concrete bridge decks and asphalt road surfaces are constantly exposed to vehicular traffic resulting in rapid deterioration. Inspection process can be optimized by minimizing the disruption to traffic flow with the help of automation-assisted techniques (Gucunski et al., 2015). In addition to highway and bridge inspection, pipeline inspection is another area that benefits from automated technologies (Agrawal et al., 2008; Chae & Abraham., 2001; Ékes, 2016; Ékes et al., 2011; Halfawy & Hengmeechai, 2014; Kwak et al., 2007; Moradi & Zayed, 2017; Painumgal, Thornton, Uray, & Nose, 2013) as traditional methods such as Closed-Circuit Television (CCTV)-based and manual inspection are not capable of producing accurate quantitative account of the pipe defects, especially the non-surface defects. Moreover, these methods are subjective and often result in inaccurate condition assessments due to

the operator skills and biases (Ékes, 2016; Kwak et al., 2007). However, technologies such as Laser Detection And Ranging (ladar), lidar, Sound Navigation And Ranging (sonar), Ground Penetrating Radar (GPR), infrared imagery, and gyroscopy, when used in combination with conventional technologies, produce a fairly accurate account of pipe dimensions and sediment depth (Ékes et al., 2011; Javadnejad, Simpson., Gillins, Claxton, & Olsen., 2017). Underground tunnels and power lines are also examples of networked infrastructures requiring regular maintenance. However, the complex buried environment makes their inspection and maintenance challenging, time-consuming, and expensive (Protopapadakis et al., 2016). To address some of these issues, laser sensors and scanners, and Red Green Blue (RGB) cameras have been used for tunnel inspection (Protopapadakis et al., 2016). Jiang, Sample, Wistort, & Mamishev (2005) explored using similar technologies in combination with lidar for the condition assessment of underground power lines, and Larrauri, Sorrosal, & González (2013) used UAVs equipped with video and an Infrared (IR) thermal camera to inspect overhead power lines.

The application of automation-assisted condition assessment technologies is not limited to networked infrastructures. Researchers have also explored the possibility of using these advanced technologies to inspect dam structures and penstocks (Özaslan et al., 2016; Ridao, Carreras, & Ribas, 2010), nuclear reactors (Cho et al., 2004; Dong, Chou, Fang, Yao, & Liu, 2016), and oil and gas refineries (Steele et al., 2014) as well as for crack detection in buildings and masonry walls (Eschmann et al., 2012; Lins & Givigi, 2016). More specifically, UAVs, Micro Aerial Vehicles (MAVs) and autonomous underwater vehicles equipped with sensors such as cameras, IR cameras, and pressure

sensors have been used for concrete crack detection and dam structure inspection; nuclear power reactors have been inspected using remotely operated vehicles to protect inspectors from possible radiation exposure (Dong et al., 2016), and oil and gas refinery inspection robots have been equipped with methane gas sensors that detect possible gas leakage (Steele et al., 2014).

Not only routine inspections but also post-disaster inspection procedures can be expedited with the use of automation. Manual inspection is time-consuming and often not safe under a post-catastrophic condition. Using remotely operated technologies such as tele-operated robots and UAVs can improve the overall efficiency, accuracy, and safety of the inspector (Murphy et al., 2011; Torok et al., 2013). For example, Murphy et al. (2011) investigated how Unmanned Marine Vehicles (UMVs) could improve the inspection process of a bridge in Texas in the aftermath of Hurricane Ike. Furthermore, Dabove, Di Pietra, & Lingua (2018) investigated the possibility of using tablet technology to capture images in a post-earthquake scenario.

### *Sensors and technology*

The sensors used for data collection can be broadly classified into two categories: those used for inspection and those used for navigation and control. The sensors used for inspection range from cameras to vibration detectors. As this review focuses only on articles exploring visual inspection techniques, the automated technologies analyzed here included RGB still or video cameras. Additionally, CCTV-based images and videos were used for underground pipe and sewer inspection applications (Chae & Abraham., 2001; Ékes, 2016; Ékes et al., 2011; Halfawy & Hengmeechai, 2014; Kwak et al., 2007; Moradi

& Zayed , 2017). Other technologies such as GPR, sonar, lidar, optical scanner and gyroscope were also used to improve the data collection (Ékes, 2016; Gucunski et al., 2015; Moselhi et al., 2017). Moselhi et al. (2017) used a combination of GPR and IR technology for bridge defect detection. In addition, GoPro cameras and commercially available off-the-shelf digital cameras were used for visual data collection (Ellenberg, Kotsos, & Moon, 2016; Ellenberg et al., 2016; Henrickson et al., 2016; Khaloo et al., 2018; Khan et al., 2015). For bridge inspections, the equipment used in combination with video/still camera included impact echo to detect surface delamination; electrical resistivity measures and GPR techniques to characterize corrosive environment and to locate rebar corrosion (Gucunski et al., 2015); lidar scanners to assess surface conditions such as cracks, spalls, scaling and roughness (Eschmann & Wundsam, 2017; Harris et al., 2016); IR imagery and radar to locate subsurface anomalies and defects (Harris et al., 2016); IR laser projector to obtain depth information from RGB images (Ellenberg et al., 2014); and seismic/acoustic sensor array for crack detection (La et al., 2013a). IR thermal imaging techniques were used in power line inspection and management to detect excessive heat buildup (Larrauri et al., 2013). Further, this technology was also used in bridge inspection application (Hiasa et al., 2018) and general infrastructure application (Rea & Ottaviano, 2018). Additionally, long wavelength IR technology is used to detect and classify humidity (Eschmann Christian & Wundsam Timo, 2017). A 3D model embedded with georeferenced environment was developed to support realistic inspection and navigation. Terrestrial lidar technology was even used for generating point clouds for Civil Integrated Management (CIM) model (Javadnejad et al., 2017). Further, lidar technology was also used to measure

cross sectional shape and for centroid alignment (Vong, Ravitharan, Reichl, Chevin, & Chung, 2017). In addition, dielectric sensors were used to detect the presence of water in cable insulation, and acoustic sensors are used to measure partial discharge (Jiang et al., 2005).

The sensors used in oil and gas refinery inspection include microphones for acoustic sensing of leaks and explosions, methane gas sensors for the detection of toxic gases and thermal cameras (Steele et al., 2014). Other sensors used for data collection include water leakage sensors and temperature and pressure sensors in dam and penstock inspections. Sensors used for navigation purposes include but are not limited to GPS, video/still cameras, Doppler velocity logs, motion sensors, gyroscopes, accelerometers, magnetometers, inertial navigation systems (comprised of gyroscope, accelerometer and magnetometer), pressure sensors, laser and ultrasonic sensors, and motion planning sensors (Ridao et al., 2010). Additionally, Rea and Ottaviano (2018) used magnetic field sensor and gravity sensor for navigation purpose. Moreover, underwater autonomous inspection robots are equipped with buoyancy modules and echo sounders (Dong et al., 2016).

However, not all the papers detailed the sensors used for defect detection and navigation purposes. If the study objective was algorithm development/enhancement, the description of the technology investigated was not very well-developed. Instead, it focused on algorithm testing and validation. For example, Halfawy and Hengmeechai (2014) developed a novel algorithm to automatically identify, locate and extract regions of interest (ROI) based on camera motion without including a detailed account of the technologies used in their study.

### *Levels of automation*

Automating a system means that a function previously carried out by human operators is fully or partially replaced by a machine/computer. Based on the extent of involvement by the machine in relation to the involvement of the human, Sheridan (2002) categorized automated systems into 8 categories (Sheridan, 2002; Wickens, Gordon, Liu, & Lee, 2003). According to Sheridan (2002), different dimensions represented by these scales are: the degree of specificity required for inputting requests to the machine by humans; the degree of specificity with which the system communicates results or recommendations with human; the degree to which human is responsible for initiating actions; and the timing and detail of feedback to the human after machine takes action. Classification of reviewed articles based on this scale may not be perfect, because, it is solely based on the qualitative information available in the articles. No metrics were taken into account for the purpose of categorizing the articles reviewed into different levels of automation. Not all articles reviewed here could be classified into one of these categories because the tasks carried out by human and machine were not distinctly defined or explained. However, with the limited information available, they were classified based on the level of automation framework developed by Sheridan and Wickens et al. ( Sheridan, 2002; Wickens et al., 2003). Additionally, different aspects of a single technology may call for different levels of automation. For example, if the inspection system is capable of collecting data autonomously, but requires manual data analysis, the data collection module will fall into a higher automation category than data analysis module. Identifying automation assisted systems into different categories will potentially help develop training



strategies for inspectors. Additionally, the system designer can decide what tasks need to be automated and what tasks need to be manually controlled. Knowing this in advance will help operators prepare for any kinds of automation failures. Table 2.3 presents the classification of the articles based on their level of autonomy.

Table 2.3. Levels of Automation(Sheridan, 2002; Wickens et al., 2003) and classification of articles

Level	Role of automation and human	Articles
1	Automation offers no aid; Human in complete control.	None
2	Automation suggests multiple alternatives, filters and highlights what it considers to be the best alternatives.	Chen et al., 2011; Dabove et al., 2018; Dong et al., 2016; Ellenberg, Kontsos, Bartoli, & Pradhan, 2014; Gucunski et al., 2015; Harris et al., 2016; Henrickson et al., 2016; Hiasa et al., 2018; Khaloo et al., 2018; Moselhi et al., 2017; Villarino et al., 2014; Wang et al., 2017
3	Automation selects an alternative, one set of information, or a way to do the task and suggests it to the person.	Attard, Debono, Valentino, & Di Castro, 2018; Ékes, 2016; Ékes et al., 2011; Ellenberg et al., 2014; Ellenberg, Kontsos, & Moon, 2016; Ellenberg et al., 2016; Eschmann Christian & Wundsam Timo, 2017; Eschmann et al., 2012; Fujita et al., 2017; Hackl et al., 2017; Halfawy & Hengmeechai, 2014; Javadnejad Farid et al., 2017; Larrauri et al., 2013; Lee, Kim, Kim, Myung, & Choi, 2012; R. G. Lins & Givigi, 2016; Moradi Saeed & Zayed Tarek, 2017; Protopapadakis et al., 2016; Son et al., 2014; Wang & Birken, 2015; Yeum et al., 2017
4	Automation carries out the action if the person approves.	Attard et al., 2018; Cho et al., 2004; La et al., 2013a; Romulo Gonçalves Lins et al., 2018; Merz & Chapman, 2011; Murphy et al., 2011; Özaslan et al., 2016; Rea & Ottaviano, 2018; Vong et al., 2017; Yoder & Scherer, 2016
5	Automation provides the person with limited time to veto the action before it carries out the action.	None
6	Automation carries out an action and then informs the person	Gucunski et al., 2015; Jiang et al., 2005; Lim et al., 2014; Painumgal et al., 2013; Reed, Wood, Vazquez, & Mignotte, 2010; Ridao et al., 2010; Steele et al., 2014
7	Automation carries out an action and informs the person only if asked	None

8	Automation selects method, executed task, and ignores the human (the human has no veto power and is not informed)	None
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As this table shows, none of the articles surveyed in this review exemplify Level 1 (computer offers no aid, human completes all the tasks) nor Levels 7, 8 (computer carries out all the tasks without any human involvement). If the automated system suggests multiple alternatives, highlighting what it considers to be the best alternative, it is considered Level 2 automation. An example of such a system is a robot that merely displays and highlights the data it collected after preliminary analyses. More specific examples of Level 2 autonomous systems include the data visualization module of the bridge deck inspection robot Robotics Assisted Bridge Inspection Tool (RABIT) (Gucunski et al., 2015), remote sensing technologies used for bridge deck inspection (Harris et al., 2016), image processing techniques providing texture variation (Henrickson et al., 2016) and the UAV-based bridge assessment system explained in Khan et al. (2015). The image fusion technique combining IR and GPR images and the data processing techniques such as histogram equalization, threshold, edge detection, subtraction and image segmentation used to improve the accuracy of bridge condition assessment is also an example of Level 2 automation as these techniques highlight what it considered to be the best alternative (Moselhi et al., 2017).

The LADAR-based pipeline inspection method explained by Kwak et al. (2007) is also an example of Level 2 automation, with the robotic system collecting and providing the data to the inspector for analysis. The data management and visualization system of

the ultrasonic crawler robot used for pipe inspection, also an example of Level 2 automation, filters and highlights critical areas as do the 3D point cloud images of curtain walls generated using lidar (Liu, Jenness, & Holley, 2016). In addition, the technologies such as 2D and 3D photogrammetric modeling and laser scanning used to generate 3D point cloud models for infrastructure systems (Khaloo et al., 2018; Villarino et al., 2014) and the photo enhancement techniques used to improve the images for viewing and measurement purposes are also considered Level 2 automation (Chen et al., 2011). Dabove et al. (2018) also used 3D point clouds generated from images captured using tablets for post-earthquake inspection. The remotely operated vehicle deployed for the inspection of nuclear reactor vessels is controlled by the operator using the camera information collected by the robot (Dong et al., 2016). This system highlights what is important on the site and the controller makes the ultimate decision, meaning Remotely Operated Vehicle (ROV) is categorized as Level 2. The camera based inspection system mounted on a car to inspect catenary bridges is an example of Level 2 automation because the system doesn't process the image data. It merely displays the images collected (Wang et al., 2017). Similarly, the bridge inspection drone explained in Hiasa et al. (2018) is also an example of level 2 system, because the drone is manually controlled and the data is manually analyzed.

For Level 3, the automation selects one alternative and presents it to the inspector. Examples of this level include the GPR system (Ékes et al., 2011) and the pipe inspection system that accurately calculates the sediment volume and pipe dimensions (Ékes, 2016). Algorithms developed to detect cracks/damages, to plan paths, to detect sediment volume and to control the robot are also examples of Level 3 automation. These algorithms process

and analyze the data, providing the operator with one best answer or solution. Examples of such algorithms are the crack detection algorithm that provides inspectors with exact locations of cracks (Torok et al., 2013), the crack detection algorithm used in bridge inspection for identifying cracks (Ellenberg, et al., 2014; Ellenberg et al., 2014; Eschmann & Wundsam, 2017) and to detect cracks in tunnels (Protopapadakis et al., 2016), automatic ROI and debris detection algorithms (Halfawy & Hengmeechai, 2014), the crack detection algorithm used to detect bridge-related damages (Ellenberg et al., 2016), the artificial neural network algorithm used to detect cracks in sewer pipelines (Chae & Abraham., 2001), the hidden Markov model based on Viterbi algorithm to detect sewer pipeline defects (Moradi & Zayed, 2017), the decision tree algorithm used for the determination of rusted surface and blasting areas of steel bridges, the algorithm based on machine learning for detecting cracks in asphalt pavement using surface imagery (Fujita et al., 2017), the data analysis module of the Versatile Onboard Traffic Embedded Roaming Sensors (VOTERS) mobile sensor system used for surface and subsurface assessment of roadways (Wang & Birken, 2015), the delamination identification algorithm used to identify damages from images from UAVs on steel bridge surfaces (Ellenberg, Kontsos, & Moon, 2016), the automated image localization technique developed to extract regions of interest on images taken by UAV cameras (Yeum et al., 2017), the color restoration and target detection algorithms used for underwater applications (Lee et al., 2012), and the image processing, crack detection and edge detection algorithm used for building inspection (Eschmann et al., 2012). Further, the computer vision technique, Tinspect, explained by Attard et al. (2018) is also an example of Level 3 automation as they investigated the possibility of

using various image processing and change detection methods to inspect the changes on the large hadron collider (LHC) tunnel linings. The processed images help the inspector identify any changes to the tunnel linings.

The autonomous robotic system used for structural health monitoring is also an example of Level 3 automation as it triggers an alarm to inform users of the condition of the structure (Lins & Givigi, 2016). Further the Structures from Motion (SfM) method explained by Javadnejad et al. (2017) is also an example of Level 3 automation extracting pipe features with minimal supervision based on point clouds established. Hackl et al. (2017) developed a Level 3 automation system to generate fluid dynamic simulations from topographic images collected using UAVs. This technology helps inspectors determine the hydraulic stability of the structure based on the computational fluid dynamic simulations. Since, this technique only aids decision making by developing model, it is categorized as a Level 3 system.

In a Level 4 system, the robotic system carries out actions after the operator approves them. The autonomous robotic system used for bridge inspection is an example of Level 4 automation. It uses an Extended Kalman Filter (EKF) for localization, and a motion planning and control algorithm generates a path for the robot to follow (La et al., 2013a). The robotic system explained by Lins et al. (Lins et al., 2018), used for structural health monitoring, uses Vision-Based Measurement (VBM) algorithm and Velocity Estimation (VE) algorithm to measure obstacle in its trajectory and to control its trajectory. Further, it is capable of processing the data to detect and measure crack information. These features make it a Level 4 automation system (Lins et al., 2018). The KeproVt, underwater

robot used for nuclear vessel inspection also uses a path generation algorithm. Even though the robot is manually controlled by hand-held devices, its path is generated by the algorithm (Cho et al., 2004). Other underwater marine systems used for inspection after Hurricane Ike were also Level 4 systems as they are capable of performing inspections both manually and automatically (Murphy et al., 2011). Similarly, the robotic system used for general infrastructure inspection is also an example of Level 4 system because it has both teleoperated and autonomous modes. Additionally, it generates 3D scans of the data collected (Rea & Ottaviano, 2018). Further, the UAS, capable of performing both autonomous and semi-autonomous inspection, used for railway and tunnel inspection is also an example of level 4 automation (Vong et al., 2017). Another example is the MAV used for dam inspection, a system controlled by an operator using an RC interface based on the position estimation result calculated by the algorithm (Özaslan et al., 2016). Micro aerial vehicles, also Level 4 automation systems, have been used to conduct autonomous exploration and to develop 3D models for bridge structures with minimal input from the operator exhibiting performance as good as a system controlled by a skilled pilot (Yoder & Scherer, 2016). Another example of a Level 4 aerial automation system is the autonomous unmanned helicopter system used for infrastructure inspection. This system is controlled by a pilot who provides commands for flight operations (Merz & Chapman, 2011). The oil and gas refinery inspection robot detailed in Steele et al. (2014) is teleoperated by an operator who gives high level commands directing the robot to a particular point. This Level 4 robotic system then automatically collects the data using sensors (Steele et al., 2014).

Highly automated Level 6 systems carry out all the actions autonomously while keeping the operators informed about the actions, one example being the PICTAN pipe inspection system. The position estimation algorithm used in the system calculates the position of a pipe inspection robot based on the images it captures (Painumgal et al., 2013). In addition, the bridge inspection Robotic Crack Inspection and Mapping (ROCIM) robotic system, another example of a Level 6 system, carries out inspection tasks using a path planning and a crack detection algorithm (Lim et al., 2014). Another example of Level 6 automation is the ship hull and harbor inspection robot capable of conducting inspection tasks autonomously using tracking and anomaly detection algorithms, real-time 3D reconstruction techniques and dead-reckoning navigation. The operator can take control of the robot with a joystick if the automation fails (Reed et al., 2010). The robotic system used for the inspection of underground cable systems, another example of Level 6 automation, keeps the inspector informed of the sensor output data through a user interface in the autonomous mode (Jiang et al., 2005). A tunnel inspection monorail (TIM) used to investigate LHC tunnel is an example of Level 6 automation as it collects images without any human intervention (Attard et al., 2018). The autonomous underwater vehicle used for the visual inspection of hydraulic dam also falls in the category of Level 6 automation as the intelligent control architecture controls the system autonomously with the help of sensors and a perception module (Ridao et al., 2010).

*Navigation and control*

It is important that the navigation and control technologies and their user interfaces of automated infrastructure systems are easy to understand and useful for the maintenance personnel as complicated technologies and user interfaces can lead to reduced utility. Articles analyzing automated technology provided a detailed account of the navigation and control system; however, those focusing on data extraction and representation provided only a vague explanation of the data collection techniques and the navigation and control strategy used. Fully autonomous robotic systems rely on the data from GPS and/or IMU units (Ellenberg, et al., 2014; Ellenberg, et al., 2016; Gucunski et al., 2015; Henrickson et al., 2016; Khaloo et al., 2018; R. G. Lins & Givigi, 2016), with path planning algorithms using these data as input to develop a path for the robots to follow (Gucunski et al., 2015; R. G. Lins & Givigi, 2016). VBM and VE algorithms have also been used to implement navigation strategies and to control robot's trajectory (Lins et al., 2018). GPS capability was used to create waypoints to define routes for the robots (Henrickson et al., 2016; Javadnejad Farid et al., 2017; Merz & Chapman, 2011; Murphy et al., 2011); however, constrained indoor, dark and featureless conditions such as penstocks, underground tunnel and pipe systems, and underwater environments do not allow for access to such external positioning systems (GPS and satellite) (He, Prentice, & Roy, 2008; Özaslan et al., 2016). Other navigation technologies can be used for autonomous/manual navigation of the robotic systems under such unfavorable conditions. For example, Özaslan et al. (2016) used a Proportional Derivative (PD) controller for the navigation and control of an MAV in a dam penstock. The operator controlled the robot by defining the waypoints using a remote-control interface. Eschmann and Wundsam (Eschmann & Wundsam , 2017) used



a miniaturized lidar for navigational purpose. A camera, IMU and 2 lidars were used for indoor localization. Navigation sensors such as depth gauges, gyroscopes, magnetometers and sonar have been used to navigate a remotely operated underwater vehicle (ROV) for nuclear reactor pressure vessel inspection (Dong et al., 2016), and Ékes Csaba et al. (2011) and Javadnejad et al. (2017) used an Inertial Navigation System (INS) along with lidar data to map the coordinates of an underground pipe.

In addition to these sensors taking linear and angular measurements, optical sensors are used for position estimation and navigation tasks. Protopapadakis et al. (2016) used visual images and laser technology for navigating an autonomous mobile vehicle with a robotic arm within a tunnel system. The position of a pipeline inspection autonomous underwater vehicle (AUV) was estimated using cone laser and fisheye camera technology. These images were fed to a position estimation algorithm to calculate the precise position of the robot. Moreover, video transmitted through fiber optic cable was used for status information and remote operation of an ultrasonic crawler robot for buried pipe inspection. However, in some underground applications, the multi-sensor pipe inspection system was controlled by an operator pulled through the system using a tethered rope (Ékes, 2016). Moreover, in some underground pipeline applications, a skilled operator moves the CCTV camera at a relatively constant speed, capturing images of the pipe's internal surface (Chae & Abraham, 2001; Halfawy & Hengmeechai, 2014).

The robotic systems reviewed in this literature survey were typically tele-operated or were able to complete the mission without human intervention although even those systems characterized as completely autonomous were monitored by a human operator.

Remotely operated inspection systems were controlled using joysticks, remote interfaces, remote controllers and other handheld devices such as a mouse and a touchpad, while advanced automated technologies used for inspection were capable of completing inspection and navigation tasks both autonomously and non-autonomously. For example, Gucunski et al. (2015) investigated the implementation of a fully autonomous robotic platform for bridge inspection that moved along the path specified by a path planning algorithm. However, such robotic systems were additionally controlled using keyboards, joysticks and android/iPhone devices in manual mode (Gucunski et al., 2015). An autonomous robotic system used for underground cable inspection was capable of carrying out operations autonomously with the help of control module. Additionally, an operator was able to view the sensor output through a user interface and controlled the operations remotely in the event of automation failure (Jiang et al., 2005). Protopapadakis et al. (2016) also used a similar strategy to control an autonomous robot inspecting tunnels. Although an integrated global system controlled the overall operation and mission execution, the user was able to view the inspection information on the user interface and was kept informed of the inspection task (Protopapadakis et al., 2016). An oil and gas inspection robot developed by Steele et al. (2014) was also capable of completing inspection tasks in both tele-operated and completely autonomous modes. In the former, the inspector used a teleoperation camera in combination with a joystick, while in the completely autonomous mode, the operator provided high level commands to the robot (Steele et al., 2014). The Seekur mobile robotic platform used for bridge inspection also had multiple control modes: manual, semi-autonomous and completely autonomous, with a GUI displaying the robot

data and sensor data for monitoring and control purposes (La et al., 2013a). The underwater dam inspection system detailed in Ridao et al. (2010) also involved multiple control modes: a tethered remotely operated mode, and an untethered autonomous mode with the perception module and the intelligent control module operating the robot under completely autonomous operations (Ridao et al., 2010). Tracking Hybrid Rover for Overpassing Obstacles (THROO) mobile platform used for general infrastructure inspection was also capable of completing the inspection task in both tele-operated and autonomous modes. The article explored only teleoperation capability for infrastructure inspection. In tele-operated mode, the operator received the data collected using the sensors on a tablet for understanding the environment.

A waypoint navigation technique has been used to navigate a remotely operated vehicle (ROV) used for harbor inspection. A mission planner module ensured the movement of the vehicle along a specified path under autonomous mode, while under manual mode, an operator controlled the system with the help of a joystick (Reed et al., 2010). In addition, control algorithms ensured trajectory control by keeping a structural health monitoring (SHM) robot on track (Lins & Givigi, 2016). Ellenberg et al. (2014) used a third generation Apple iPod touch to control a UAV for quantitative evaluation of infrastructure. The controller was able to view the images and videos sent to the controlling device while flying the UAV. Researchers also used an artificial potential field approach to control the robot and to keep it on track. An inspection robot followed the attractive force created by a virtual robot during a bridge inspection task in La et al. (La et al., 2013b). Moreover, microcontrollers and PD controllers were used to control the position of a pipe

inspection robot (Painumgal et al., 2013), and MAVs inspecting a dam penstock (Özaslan et al., 2016) and a train bridge (Yoder & Scherer, 2016). Further, TIM used for tunnel inspection used an encoder fitted to its track to measure the distance travelled and its position. Further, a position barcode was used to avoid cumulative errors (Attard et al., 2018).

Automated unmanned aerial systems such as drones and MAVs completed inspection task in autopilot mode with takeoff and landing controlled manually (Henrickson et al., 2016; Yoder & Scherer, 2016). While performing the inspection task, the UAV followed a predetermined path specified by the controller using waypoint navigation (Henrickson et al., 2016). In addition, the autonomous helicopter used in the remote sensing application was capable of completing inspection tasks autonomously with the landing task controlled manually. This helicopter was additionally equipped with manual control capability. The controller could operate the helicopter using an RC transmitter in the manual mode (Merz & Chapman, 2011). Further, the UAS used for railway culvert and tunnel inspection had both autonomous and semi-autonomous mode (Vong et al., 2017). The autonomous mode used a commercially available flight controller. In the semi-autonomous mode, the flight was controlled using a proportional-integral-derivative (PID) controller (Vong et al., 2017). However, not all UAV systems surveyed in this paper were automated. For example, the UAVs used for quantitative assessment of highway bridges (Ellenberg, Kotsos, & Moon, 2016) and curtain wall inspection (Liu et al., 2016) were controlled manually by the pilot. The UAV used for remote building inspection and monitoring tasks was controlled manually by a pilot although it also had a

semi-autonomous mode (under pilot supervision) supported by GPS-guided waypoint navigation (Eschmann et al., 2012). The ROV examined by Dong et al. (2016) was controlled manually by a remote operator through a user interface displaying camera information, joysticks and peripheral buttons or handheld controllers. Finally, the ground robot platform used for post-disaster building assessment was controlled by a remote operator with the help of a high-resolution camera. However, the data collection and transmission were driven by an autonomous algorithm (Torok et al., 2013).

### *Algorithms*

Various types of algorithms were used in automation assisted visual infrastructure inspection techniques. Table 2.4 lists the algorithms used in the articles reviewed in this survey.

*Image recognition:* An image recognition algorithm was used in autonomous robotic tunnel inspection (Protopapadakis et al., 2016) and an Iterative Closest Point (ICP) algorithm was used in the fully autonomous visual inspection of dam penstocks (Özaslan et al., 2016). Horn's method used a 3D coordinate transformation (Yeum et al., 2017). In automated systems for overhead power line inspection using an unmanned aerial vehicle, researchers used an artificial vision algorithm to locate edges and estimate distances (Larrauri et al., 2013). In addition, a three dimensional optical bridge-evaluation system (3 DOBS) algorithm (close range photogrammetry) was used in service bridge field performance remote sensing image recognition (Harris et al., 2016).

*Navigation:* Control algorithm (coordinate between sensors and navigation) and Extended Kalman Filter (EKF) based navigation were used in robotic bridge deck inspection (La et

al., 2013a). In a second example of bridge deck inspection, Gucunski et al. (2015) used a path planning algorithm for robotic vehicle navigation. An effective 3D path planning algorithm with surface frontier #D surface exploration and incremental path planning algorithms were used in the inspection of the infrastructure of a train bridge in conjunction with a micro-aerial vehicle (Yoder & Scherer, 2016). In another example of bridge deck crack detection, a Robotic Inspection Plan (RIP) Genetic Algorithm (GA) and RIP greedy algorithms for path finding were tested (Fujita et al., 2017), with the results indicating that the GA performed better than the RPI greedy algorithm for automated pathfinding (Fujita et al., 2017). Further, an EKF for navigation with wall detection and tracking algorithms was used in autonomous underwater vehicle for dam monitoring (Ridao et al., 2010). Several algorithms have been developed for depth detection as it is important in underwater conditions. For example, one such algorithm was used for depth detection of a nuclear reactor pressure vessel and other water-filled infrastructures (Dong et al., 2016). In addition, AUVs used a real-time position estimation algorithm and an offline position estimation algorithm for in service pipeline inspection (Painumgal et al., 2013). Centroid location algorithm is an example of position control algorithm used to align UAS with the centroid of inspection structure (Vong et al., 2017). Lins et al. (2018) used VBM and VE to control robot's trajectory. Rea and Ottaviano (Rea & Ottaviano, 2018) used a control algorithm to achieve interoperability of multiple sensors.

*Image processing and detection:* Image detection and enhancing algorithms have been used to detect an area of interest or to increase the image quality. After capturing images, to automatically detect cracks Eschmann and Wundsam (Eschmann & Wundsam, 2017), Lins

et al. (2018), and Torok et al. (2013) used a crack detection algorithm. Further, Torok et al. (2013) used an aerial direction algorithm with orthonormal axes. In addition, Eschmann and Wundsam (Eschmann & Wundsam, 2017) visualized humidity data collected using and Long Wavelength Infrared (LWIR) sensors as a superficial layer. Researchers used a #D information extraction algorithm to process images and to detect cracks (Protopapadakis et al., 2016). Random sample consensus algorithm (RANSAC algorithm) was used for extracting pipe features. In addition, images taken underwater have to be processed and enhanced to improve their quality. Color restoration, template matching (target object detection) and mean shifting (object tracking) algorithms were used for underwater infrastructure monitoring (Lee et al., 2012). For bridge-related damage detection, a UAV camera calibration algorithm and homograph image flattening were used in a crack detection algorithm along with K-means (Ellenberg, et al., 2016). Further, for image processing, pattern recognition techniques, a crack detection algorithm and edge detection algorithms were used in UAV building inspection and monitoring (Eschmann et al., 2012). In addition, to identify important markers such as cracks or tears, a measurement algorithm was used in quantitative infrastructure evaluation (Ellenberg, et al., 2014). Additionally, images from multiple NDT sources were fused to produce a more accurate picture of inspection site using a wavelet transform technique. Various image processing techniques were also applied to the images prior and/or after fusing to improve the accuracy of bridge condition assessment (Moselhi et al., 2017).

*Defect detection:* Defect detection algorithms have been used to identify possible defects present in an infrastructure. For example, fuzzy logic based artificial neural network

algorithms were used in sewer inspection (Chae & Abraham., 2001). This algorithm computed input-preprocessed data and output-attributes of cracks such as number and dimensions. Further, for a rust classification model, Support Vector Machine (SVM), Back-Propagation Neural Network (BPNN), Decision Tree (J48), Naive Bayes (NB), Logistic Regression (LR), and K-Nearest Neighbors (KNN) methods were used (Son et al., 2014). A control algorithm, vision-based measurement algorithm (relative pose of target) and crack detection and crack measurement algorithms were used in an automated structural health monitoring robot (Lins & Givigi, 2016). In addition, for corrosion detection, a convex hulling algorithm and an iterative closest point algorithm were used to calculate the area and perimeter of corrosion (Kwak et al., 2007). Crack detection algorithms were also used in a pavement inspection application. For machine learning for asphalt crack detection, Hilditch's algorithm was used to detect centerlines of the cracks in conjunction with a pixel level classification F measure for crack detection (Fujita et al., 2017).

Table 2.4. Algorithms used in the articles reviewed

Algorithms	Articles
Artificial Neural Network	(Chae Myung Jin & Abraham Dulcy M., 2001)
Tracking Algorithm	(Cho et al., 2004; Lee et al., 2012; Ridao et al., 2010)
Iterative Closest Point Algorithm	(Kwak et al., 2007; Özaslan et al., 2016)
Automatic Target Recognition Algorithms	(Reed et al., 2010)
Kalman Filter	(La et al., 2013a; Ridao et al., 2010; Steele et al., 2014; Yoder & Scherer, 2016)



Color Restoration Algorithm	(Lee et al., 2012)
Pattern Recognition	(Eschmann et al., 2012)
Crack Detection	(Ellenberg, et al., 2016; Eschmann & Wundsam, 2017; Eschmann et al., 2012; Fujita et al., 2017; R. G. Lins & Givigi, 2016; Romulo Gonçalves Lins et al., 2018; Protopapadakis et al., 2016; Torok et al., 2013)
Edge Detection	(Attard et al., 2018; Ellenberg et al., 2014; Eschmann et al., 2012; Larrauri et al., 2013)
Artificial Vision Algorithm	(Larrauri et al., 2013)
Arial Detection Algorithm	(Torok et al., 2013)
Position Estimating Algorithm	(Painumgal et al., 2013)
Measurement Algorithm	(Ellenberg et al., 2014)
Support Vector Machine	(Halfawy & Hengmeechai, 2014; Son et al., 2014)
Back Propagation Neural Network	(Son et al., 2014)
Decision Tree	(Son et al., 2014)
Naïve Bayes	(Son et al., 2014)
Logistic Regression	(Son et al., 2014)
k-Nearest Neighbors	(Ellenberg, Kotsos, & Moon, 2016; Ellenberg, et al., 2016; Son et al., 2014)
Nearest Neighbor	(Dabove et al., 2018)
Monte Carlo	(Lim et al., 2014)
Laplacian of Gaussian	(Lim et al., 2014)
Navigation	(Steele et al., 2014; Yoder & Scherer, 2016)
Path Planning	(Gucunski et al., 2015)
Vision Based Measurement Algorithm	(Lins & Givigi, 2016)
Information Extraction	(Protopapadakis et al., 2016; Yeum et al., 2017)
Hilditch's Algorithm	(Fujita et al., 2017)
Random Sample Consensus Algorithm	(Javadnejad et al., 2017)
Hidden Markov Model	(Moradi & Zayed, 2017)
Velocity Estimation Algorithm	(Lins et al., 2018)

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## DISCUSSION

Infrastructure inspection is receiving increased research attention because of the advancement of automated technologies and smart sensing systems. Conventional infrastructure inspection methods are time-consuming and expensive. Moreover, they can expose the inspection team to a dangerous inspection environment, putting their lives in peril (Lattanzi & Gregory, 2017). Automated inspection systems address these issues by minimizing the risk to the inspector and by improving the efficiency of the inspection process. In addition, reliance on inspectors' skills is an inherent issue associated with conventional risk inspection techniques (Ellenberg, et al., 2016), and new learning algorithms are capable of reducing this subjectivity, thereby improving the accuracy of the inspection process. Much research has explored the technological and data analytic aspects of automated infrastructure inspection. This article reviewed 53 peer-reviewed research and conference articles investigating vision-based automated inspection technologies, selected based on a systematic approach. Through this review, we tried to address a number of research questions proposed in the introduction section. The key findings are being discussed in detail in this section.

### *Validity of the system/algorithm*

Automation-assisted inspection technologies were extensively used in the inspection of highway bridges and roads. Some of these technologies were as good as or better than the existing inspection methods in terms of the accuracy of findings (Fujita et

al., 2017; Halfawy & Hengmeechai, 2014; Jiang et al., 2005; Khan et al., 2015; Kwak et al., 2007; La et al., 2013a; Liu et al., 2016; Moselhi et al., 2017; Wang & Birken, 2015; Yoder & Scherer, 2016). Moreover, Cho et al. (Cho et al., 2004) observed that the underwater robotic system developed for nuclear reactor inspection was not as time-consuming as the conventional inspection method. Although these findings are promising, more studies are needed to validate the effectiveness of these new methods in relation to the existing ones. Only eight of the 53 articles reviewed conducted a comparative analysis of new technology with conventional technology (Ellenberg, Kontsos, & Moon, 2016; Ellenberg, Kontsos, & Moon, et al., 2016; Fujita et al., 2017; Halfawy & Hengmeechai, 2014; Khan et al., 2015; Moselhi et al., 2017; Wang & Birken, 2015; Yoder & Scherer, 2016). Additionally, Javadnejad Farid et al. (2017) compared two automated methods: one based on visual images and one based on lidar scanning. Moreover, the validity and feasibility of the proposed systems/algorithms need to be evaluated through field deployment of the system. Ten of the 53 studies reported the results of laboratory-scale experiments, meaning their systems were not deployed in the field (Dong et al., 2016; Ellenberg, et al., 2014; Ellenberg, Kontsos, & Moon, 2016; Ellenberg, et al., 2016; Lee et al., 2012; Lins & Givigi, 2016; Romulo Gonçalves Lins et al., 2018; Painumgal et al., 2013; Rea & Ottaviano, 2018; Yeum et al., 2017). While Son et al. (2014) collected data by simulating the condition of a robot taking images of a bridge using a mounted camera and Steele et al. (2014) conducted preliminary studies in their mechanical room evaluating the operational capability of a refinery inspection robot, neither group of researchers completed a field study. Though lab-scale studies can confirm the validity of a proposed

system or algorithm, results from field deployments need to be analyzed to ensure ecological validity.

While most of the algorithms focused on analyzing data collected on flat surfaces like that of bridge deck or road surfaces, further research needs to be carried out to investigate the possibility of using these algorithms to investigate complex components such as joints and connections (Koch, Georgieva, Kasireddy, Akinici, & Fieguth, 2015).

#### *Human factors considerations*

None of the articles reviewed developed or investigated a completely automated system. In an automation-assisted system, the technologies remain a subordinate assisting humans with the inspection task, with human operators taking control as and when required. Most automated systems reviewed in this article have multiple control modes, meaning the operator is able to control the level of autonomy of the system. For example, the operator controls the system until it reaches the target point and then the automation controls and performs the data collection task using sensors with the help of an algorithm (Torok et al., 2013), requiring the operator to interact with the automated system. To facilitate seamless interaction between the intelligent automated system and the human, the operators should be able to provide commands/instructions in natural language (Chen & Barnes, 2014). This communication requires the inspector to be skilled at controlling complicated intelligent systems. However, none of the studies discussed the challenges or constraints posed by these systems on the operators. Understanding the initial learning curve associated with learning new technologies might help improving the system design and developing training strategies. Furthermore, it is important to investigate the perceived

satisfaction of users with the technology and its user interface to understand technology acceptance by the users. There is a need to evaluate these systems within the context specific needs of the users of these technologies to foster user acceptance and applicability (Agnisarman, Madathil, & Stanley, 2018; Agnisarman et al., 2017; Agnisarman et al., 2017; Narasimha, Agnisarman, Chalil Madathil, Gramopadhye, & McElligott, 2018; Narasimha et al., 2017).

Moreover, the communication between operators and other crew members is an important factor involved in automation control. Murphy et al. (2011) discussed the importance of having a shared understanding among the members of a team in charge of the control and operation of automation. According to them, these team members include a pilot, a payload specialist, subject matter experts and safety personnel (Murphy et al., 2011), each potentially focusing on his/her individual micro-objectives and system requirements. In such situations, it is important to have a shared understanding among team members to facilitate effective communication to achieve the overall system goal. Thus, principles of system thinking need to be considered while designing a multi-agent system operated by a team.

Furthermore, shared understanding of inspection site/workspace also needs to be studied from a post-catastrophic inspection perspective. Information overload (too much data) is an issue in emergency management scenario. This situation is complicated by multiple communication channels activated while addressing an emergency situation. However, automated systems can reduce the mental demand and cognitive load on the inspectors by sharing workspace with them. However, the automated system should be

always under the control of human to prepare him/her for any unpredictable situation (which is quite common in emergency management) (Carver & Turoff, 2007). The members of disaster management team need to be well connected with proper communication channels. System design should facilitate seamless interaction between team members working under such high pressure environment. Wearable devices can potentially facilitate communication among the team members by tracking each other's travel pattern to develop and update their inspection strategies in a dynamic environment. Furthermore, wearable devices tracking human traveling pattern can be used to develop adaptive automation systems that learn human behavior (Zhang et al., 2017). Additionally, natural language processing (NLP) technique can be employed to understand the mental demand and cognitive load on the inspectors to update the task assignment and to improve the systems adaptability (Zhang et al., 2017).

However, it is important to understand the collaborative sense-making strategy of the team members and the team SA to design a system facilitating the above mentioned interactions without having a conflict between their assigned tasks. Further research needs to be carried out to understand the team characteristics such as team cognition, SA and sense-making to inform the design of automated systems that assist post-disaster inspection. Team sense-making is defined as “the process by which a team manages and coordinates its efforts to explain the current situation and to anticipate future situations, typically under uncertain or ambiguous conditions” by Klein, Wiggins, & Dominguez (2010). A collaborative understanding of the situation is required while working as a team to achieve a common goal. The sense-making process and the nature of sense-making

depend on the situation and the experience level of the members of the team (Klein et al., 2010). Team SA is the overall SA possessed by each team member to complete the tasks assigned to him/her (Endsley, 1995b). Each of the team members need to have a really good understanding of shared elements to ensure seamless working of the system (Endsley, 1995b). Furthermore, team cognition refers to the shared knowledge or shared mental model among team members about the situation. The inspection team can have people with different levels of expertise performing a number of disparate functions such as controlling the automated system, collecting the data and developing strategies. This shared mental model can undergo changes as the team performs the inspection task (O'Connor & Johnson, 2006). Further research needs to be conducted to evaluate team cognition and how it contributes to effective team functioning (Cooke, Salas, Kiekel, & Bell, 2004).

Another important factor that needs to be considered when implementing automated inspection systems is the trust the operators have in such systems (Chen & Barnes, 2014). Too much trust can result in biases that affect the overall performance. For example, an inspector who does not verify the output from a crack detection algorithm might inaccurately report the condition of a structure. This automation bias needs to be studied from an infrastructure inspection perspective to improve the design of automated systems as well as the training of the inspectors. While inspectors are subject to automation bias, automated systems can reduce the subjectivity associated with the operator. The findings from an inspection task depend on the skills of the operator, and various operators may come up with disparate conclusions. Though the studies reviewed in this article tried to reduce the subjectivity through algorithms that automatically detect cracks or targets,

the final decision was made by the human operator, meaning the issue of subjectivity was not completely eliminated. Moreover, highly automated systems that conduct inspection tasks without any human involvement may not keep the operators in loop, affecting their SA. However, by automating the navigation task, the workload on the operators can be reduced, allowing them to focus on the inspection process, which is not automated, thus improving their SA. This division of labor will also keep the operators in the loop and facilitate their timely intervention. Further complicating the situation, the sensory perceptions of an operator controlling an unmanned system are mediated by the interface or control devices, meaning the quality of the SA depends on the system design, sensory feedback and data visualization (Riley, Strater, Chappell, Connors, & Endsley, 2010). Furthermore, since infrastructure inspection is predominantly visual involving prolonged periods of cognitive activity, operators may experience mental fatigue, which can impact their ability to concentrate on the inspection task (Boksem, Meijman, & Lorist, 2005). This decline in attention in turn affects their signal detection ability and vigilance (Raja Parasuraman, Warm, & Dember, 1987). System design needs to consider these factors to keep inspectors attentive and vigilant throughout the inspection process.

While performing infrastructure inspection, the inspector has to process and make sense of data from multiple sources. Especially in structural health monitoring, it is important to look at both the structural aspect and the qualitative condition of the building. While automation can be used to reduce this information overload, it is important to understand the sense-making process of the inspectors when developing decision aids that could potentially reduce the cognitive demands placed on them. Investigating the sense-



making strategy of individuals synthesizing this inspection data will help the designers understand how users fit the data into frame or seek more data to update the frame. If the data from multiple sources don't converge, the cognitive load and users' confidence in decision making will be negatively affected (Agnisarman, Madathil, & Stanley, 2018; S. Agnisarman, Ponathil, Lopes, & Chalil Madathil, 2018a; Madathil & Greenstein, 2018; Ponathil, Agnisarman, Khasawneh, Narasimha, & Madathil, 2017). Further studies need to be conducted to investigate the needs of the inspectors and the individual differences that would lead to variability in the inspection results.

#### *System design implications*

These human factors considerations can potentially be addressed through Wickens' information processing model, which explains how humans perceive and process information, make decisions and execute action (Wickens et al., 2003). His model involves sensation, perception, decision making and decision execution. Automated systems can be designed to intervene in any stage of this information processing (Parasuraman, Sheridan, & Wickens, 2000). Sensing systems in automated systems acquiring information from the environment are examples of automation intervening in the sensing stage. High-level automation systems can filter these data, presenting only select information. The use of such systems by operators is influenced by their reliability: lower reliability results in system disuse, while high reliability may bias the operator's decision making (Parasuraman et al., 2000). Further, automated systems assisting in the analysis stage of information processing provide extrapolation or prediction information over time (Parasuraman et al., 2000). Such systems will provide damage forecasts and possible failure modes to facilitate

inspector's decision making. However, this information could prevent the inspectors from considering alternative failure modes. Automated systems assisting in the third stage of information processing make a decision for the operator, one which he/she may or may not have the freedom to override. In the final stage, automation executes the choice of action (Parasuraman et al., 2000). However, a typical infrastructure inspection process does not involve this final stage as it usually concludes with the inspector making a decision about the type of the damage and proposing several strategies for resolving the issue.

The design of automated systems for infrastructure inspection needs to consider all the possible interaction between automation and human inspector at every stage of the inspection process. For example, in the data collection or sensing stage, over reliance on automation may prevent the inspector from looking for data that it fails to collect. Further, in the data analysis phase, the inspector might not be able to make sense of all the information collected and presented by the automated systems. None of the articles reviewed here investigated an automation system supporting the decision making phase. However, there is a potential for developing advanced automation technologies that could support inspector's decision making.

#### *Environmental conditions and technology limitations*

Though automation assisted systems can address the challenges associated with conventional inspection techniques, their application is constrained by environmental conditions. For example, use of UAVs poses a challenge to the operator in terms of their control and navigation, and UAV and underwater vehicle operation is challenging under inclement weather condition. In environments like underwater and indoor conditions where

GPS is unavailable, different navigational techniques need to be employed. In addition, the use of some of these automated systems is subject to regulations and guidelines set by federal agencies. For example, a UAV operator needs to be licensed to operate the system. These limitations need to be considered while designing automated systems to assist in infrastructure inspection.

It may not be possible to account for such environmental and weather conditions while designing an automation assisted inspection system. For example, if the surface to be investigated is wet due to a rain, the reflectance property of the surface will be changed. Such uncontrollable factors might result in erroneous inspection outcomes (Humplick, 1992). There is a need to understand how these influence errors affect inspectors' trust and attitude. Further, sensors used for data collection also suffer from several weaknesses. Visual inspection techniques relying on color cameras will not always produce accurate results because, their performance depends on the availability of light. Additionally, it is not possible to get depth information from such images unless computer vision techniques are applied (Máthé & Buşoniu, 2015). Further, poor lighting conditions limit the use of RGB cameras in dark environments like that of tunnels and buried infrastructure (Koch et al., 2015). In addition, image based inspection systems fail to produce a cross-sectional account of the structure. For example, CCTV images don't create a cross-sectional representation of the pipe structure (Kwak et al., 2007). To overcome these drawbacks, numerous other techniques ranging from radio waves to laser waves have been used. While ultrasonic and radar based technologies can be used to obtain depth information, their application is limited to lower depth or certain materials due to signal attenuation. Further,

data interpretation can also be challenging when using NDT methods (McCann & Forde, 2001). Other alternatives such as in-pipe GPR techniques need to be considered for pipe inspection application (Ékes et al., 2011). However, one of the recognized disadvantages of this technique is the attenuation of radio waves in the transition from air to ground (Klotzsche, Jonard, Looms, van der Kruk, & Huisman, 2018).

Laser scanning techniques can be successfully implemented to obtain more detailed information. Kwak et al. (Kwak et al., 2007) used 3D laser scanning techniques to develop cross-sectional profile of pipeline structure. Additionally, Khaloo et al, (2018) explored the use of lidar technology for the inspection of bridge infrastructure. However, they recognized some drawbacks to using lidar for such an application including the inability to place the scanner on unlevel terrain preventing them from scanning some regions of the bridge and the necessity of taking images from multiple scanning positions to create 3D model rendering data collection time consuming. There is a need to further the research in the domain of automated inspection to understand how these factors influence the results of the inspection as well as operators' attitude and trust in such systems.

#### *A framework for automation enabled infrastructure inspection*

Automation enabled infrastructure inspection systems can be considered as a socio-technical system involving both human and technology. Socio-technical systems function only under the involvement of human agents. Human agents are embedded within the system's architecture (Geels, 2004). Figure 2.2 is an illustration of the system engineering

framework for automation enabled infrastructure inspection. It consists of a social system, a technical system, the inspection process and influencing environmental factors. The inspection process begins with the navigation of the inspection system through the inspection environment and ends with the inspector making decisions. Social system factors considered here are the human factors determinants of automation enabled infrastructure inspection. As mentioned earlier in this paper, automated systems were introduced to address the biases and drawbacks of traditional inspection systems. Though automation enabled inspection systems are as good as or superior to traditional inspection process, there is a need to consider the challenges introduced by automation as detailed in the discussion section. Trust in automation system, SA, automation biases, use of long term and working memory, attention, perception, and inspector's skills or experience level (individual differences) with such systems are some of the human factors considerations in an automation enabled infrastructure inspection system. Further, the system interface displays an abstracted version of the complex events within the system (Degani & Heymann, 2002). Understanding users' mental model of the system events is needed while designing a system to assist them (Agnisarman, Khasawneh, Ponathil, Lopes, & Madathil, 2018).

The technical system pertains to the technical aspect of automation enabled infrastructure inspection including the material technology as well as the dynamic knowledge requirement. Various technological system issues include the drawbacks of the material technology as detailed in the discussion section, as well as the complexity of the system. Operators' knowledge in operating such advanced system is an important factor

and can be an impediment while interacting with the system. In addition, this socio-technical system dynamically interacts with the external environment. So, the environmental factors such as weather condition, feature geometry, GPS reception and site regulations also need to be considered while designing complex automated systems.



Figure 2.2. A systems engineering framework for automation enabled infrastructure inspection

## CONCLUSION

This systematic review of literature investigated articles from multiple domains including civil engineering, electrical engineering, computer engineering, mechanical and aerospace engineering, remote sensing, agricultural engineering, and industrial and systems engineering. The objectives of these articles reviewed ranged from target detection to the development of effective navigation and control technology. However, this review is not without limitations. Articles were searched using a specific set of keywords identified from an initial survey of the literature. These keywords are not comprehensive and, thus, may not have successfully retrieved all the relevant articles. In addition, only articles investigating visual inspection techniques are included in this research. The generalizability of our findings may also be limited as this review included only articles written in English. Finally, not all the articles explained the technology and data collection techniques in detail. Our understanding of data collection technique, level of autonomy and navigation and control devices is also limited to what was explained in the article as reflected in the Results section of this review. Categorization of articles into different levels of automation was solely based on the qualitative information available in the articles reviewed. There was no quantitative means to accurately categorize these articles.

Notwithstanding these limitations, this review answered the research questions proposed in the beginning. It is evident from this review that there is an increased interest in the application of automation-assisted technologies to support infrastructure inspection. Moreover, these research studies provide evidence that the use of automated systems can improve inspector safety and the efficiency of the inspection process. Furthermore, the



subjectivity of the inspector can be minimized with the help of algorithms that detect targets using the information collected by sensors, and remote or teleoperation and autonomous operation reduce the exposure of inspectors to unfavorable or risky inspection environments. However, there is a need to investigate the human factors aspects of these automation-assisted infrastructure visual inspection systems to better design the technology to meet the needs of the inspectors. Researchers need to investigate factors such as the inspectors' skills, workload demand, trust in automation, and SA from an infrastructure inspection perspective. Though these factors have received much research attention in other domains, not all the results are transferable to the infrastructure inspection domain because the maintenance personnel are not necessarily highly skilled at controlling complicated inspection systems and interpreting the quantitative data produced by such systems. Furthermore, there is a need to extend the research to post-catastrophic inspection scenario. It is important to evaluate the sense-making process of the team performing post-catastrophic inspection to inform system design. Moreover, there is a need to consider the limitations such as inclement weather conditions and policy regulations that prevent the application of these technologies in real-world conditions. To address these issues, studies need to be conducted under real-world conditions to ensure the effectiveness of the technology and its external validity.

## CHAPTER THREE

### SENSEMAKING PERSPECTIVE ON INFRASTRUCTURE RISK-RELATED MENTAL MODEL DEVELOPMENT OF WINDSTORM RISK ENGINEERS

#### INTRODUCTION

Infrastructure risk assessment, the process of inspecting civil infrastructures such as buildings, bridges and highways, is used to evaluate their current and future states, thus ensuring their functioning in the long-term as well as in the event of extreme weather conditions (Ariaratnam et al. 2001; Lattanzi David and Miller Gregory 2017). The loss prevention survey, a more specific application of infrastructure inspection found in the insurance industry, evaluates the property of clients on a regular basis to ensure the safety and stability of the structure by reducing the severity of losses (Schlesinger and Venezian 1986). Insurance companies provide several types of these loss-prevention services, including fire protection, windstorm and earthquake surveys based on the type of insurance policy.

Windstorm inspection, a visual risk assessment survey, is conducted to identify the factors that might result from severe damage in the event of such extreme weather conditions as hurricanes or tornados (“What is the Windstorm Inspection Program?,” 1999). This type of inspection is generalized and is not applicable to a specific roofing type. This survey requires the inspecting engineer to physically go to the field and collect the data needed to conduct a detailed windstorm analysis. This process is tedious and challenging as it requires inspectors to access a rooftop that may not always be easily accessible, a situation made more complicated if the client has safety regulations restricting

the inspectors from accessing it. In addition, the visual infrastructure inspection process depends on the skills of the engineer, meaning it is inherently subjective (Ellenberg et al. 2016). Moreover, not all the information needed may be available on the property site. In the absence of relevant information, inspectors are required to make engineering judgements and inferences based on their guidelines, further increasing the subjectivity of the inspection process. Finally, they may find contradictory information. In the end their decision-making depends on the guidelines and assumptions applicable to a particular situation at the time of inspection. Past research supports the difficulty of these inspections, reporting that the maximum effectiveness achieved by visual inspection is only 80% (Newman and Jain 1995).

In addition, as windstorm inspection is predominantly visual in nature, it can be influenced by the expectations generated from the inspectors' long-term memory (Hartzell and Thomas 2017) as well the mental concentration needed to maintain attention, or vigilance, for the extended period required to complete the survey. Past research has reported a decrease in the quality of sustained attention over time, a condition referred to as vigilance decrement (Parasuraman et al. 1987), meaning the quality of visual inspection over time will be attenuated, potentially impacting the accuracy of the interpretation of information. These issues can be addressed to a certain extent through the use of automated infrastructure assessment technologies to augment the capabilities of the human inspector to improve the accuracy of the inspection. For example, unmanned aerial vehicles (UAVs), one type of such technology that can assist in loss prevention risk inspection, can be equipped with sensors such as cameras, lidar, sonar, and radar to collect both

quantitative data such as dimensions and moisture content, and qualitative data such as the physical appearance and condition (Agrawal et al. 2008; Ekes 2016; Ekes et al. 2011; Eschmann et al. 2012; Gucunski et al. 2015). Computer vision algorithms further improve the efficiency of the inspection process by automating data collection and analysis processes, and path planning and navigation algorithms for automated inspection technologies improve the inspection process by minimizing the risk to the inspector (Gucunski et al. 2015; Lim et al. 2014) and by reducing the time required to conduct an inspection task (Lattanzi David and Miller Gregory 2017).

Though use of these automated systems can potentially enhance human capabilities by supporting inspectors' sensemaking process and situational awareness, there are a variety of challenges that need to be considered. Controlling and managing complex automation systems can be a difficult task for inspectors. In addition, although such technologies as non-destructive sensors are capable of collecting and analyzing the data, it is the responsibility of the inspectors to interpret this information and ultimately make the decision, a process requiring specialized skills. Thus, there is a need to investigate how these engineers make sense of the available information in order to develop effective technologies and visualization strategies that facilitate their sensemaking process without increasing the mental demand (Agnisarman et al. 2018; Agnisarman et al. 2019).

According to (Klein et al. 2007) sensemaking, the process of making sense of the information available, is a closed-loop transition between mental model formation and mental simulation. The sensemaking process, as illustrated in Figure 3.1, begins with seeking information to find an anchor to establish a useful frame, or a structure accounting

for the data. This frame/hypothesis/mental model provides shape to the data. Subsequently, more data are collected to elaborate the frame, which is then either questioned or updated based on this new information: if it contradicts the existing frame, the frame will be questioned; if it is consistent with the existing frame, the frame will be elaborated, and if the inspector is satisfied with the current frame, it will be preserved. One of the results of questioning an existing frame is reframing, a process which can lead to consideration of up to three alternative frames (Klein et al. 2007) to identify the one that best fits the data. In this research, we investigate the sensemaking process of insurance risk engineers. In addition, we investigate the challenges faced by the risk engineers while performing field inspection tasks. More specifically, we try to determine the needs of risk engineers in the design of an automated system that improves the accuracy of the inspection process by reducing the bias and inspector subjectivity. More specifically our research questions are:

- What are the steps involved in a typical windstorm inspection process?
- How do risk engineers make sense of the information available?
- What are the cues leading to the generation of initial frames?
- How do they deal with contradictory information?
- What are the challenges they encounter while completing a risk inspection task?

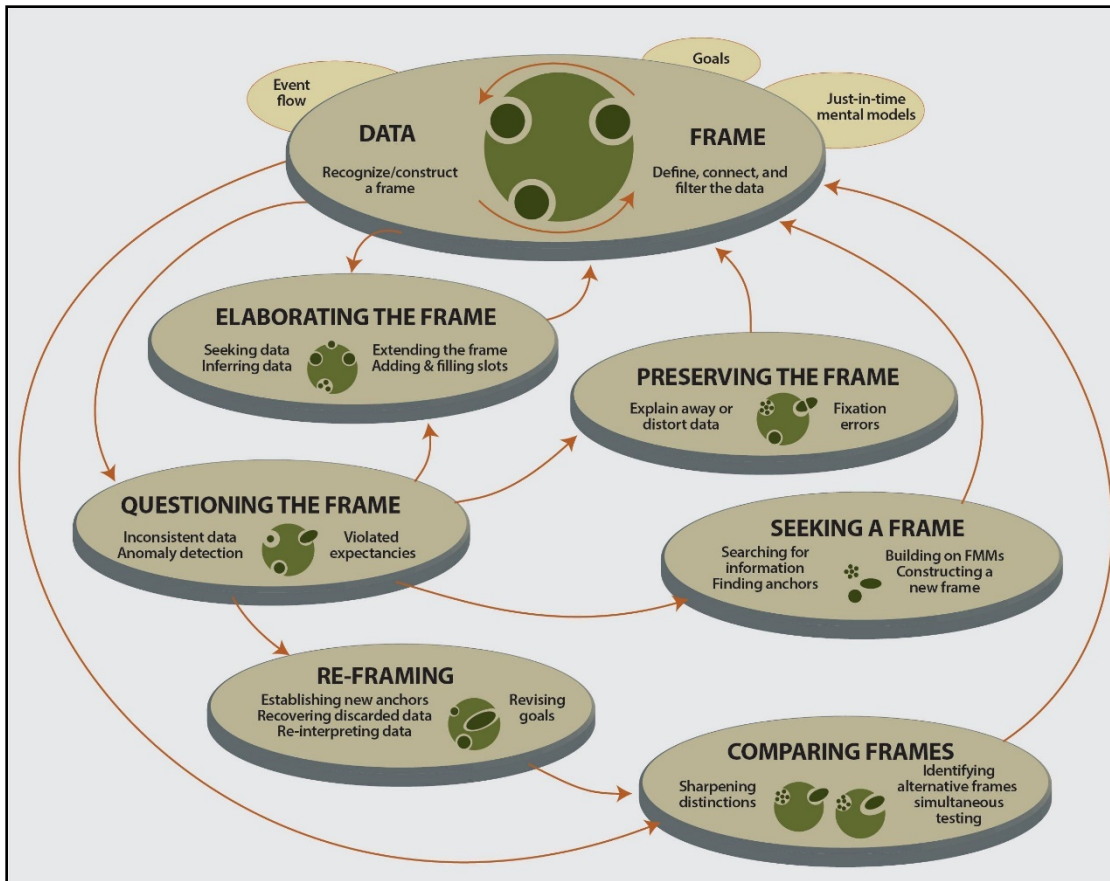


Figure 3.1. The Data/Frame Theory of Sensemaking (adapted from Klein et al., 2007)

## METHODOLOGY

Past research suggests that investigating the sensemaking process is more effective using a qualitative rather than a quantitative approach. For example, (Malakis and Kontogiannis 2013) study investigating the sensemaking process of air traffic controllers used an interview-based research methodology to explore the framing and reframing process (Malakis and Kontogiannis 2013). This approach allowed the researchers in this study to determine the underlying cognitive processes by interacting with the engineers in a more immersive manner than provided by a quantitative methodology. An interview protocol was adopted to gather data from the risk engineers through an inductive thematic

approach (Guest et al. 2012). This method is appropriate if the researcher is trying to determine themes that help to design or improve interventions or policies without developing a theory. Specific to this study the subsequent analysis involved identification of various themes from the coded transcripts (Guest et al. 2012).

### *Participants and Sampling Methodology*

This research protocol was approved by Clemson University's Institutional Review Board (IRB). The study population comprised risk engineers with windstorm experience who were at least 18 years old as the primary objective of this study was to explore the needs of this population. A combination of purposeful sampling, convenience sampling and maximum variation strategy was used to recruit participants from one of the leading insurance companies that provides property insurance services. A subject matter expert (SME) from this company was approached to help with the recruitment and research. In addition, the inclusion and exclusion criteria for participation in this study were discussed with the SME. To meet the inclusion criteria, the participants had to be at least 18 years old, have completed at least one windstorm risk inspection survey and be employed at the time of interview. Individuals not satisfying these criteria were excluded.

Since the potential purposeful sample size was not large, we adopted a maximum variation strategy to identify individuals with maximum variations in terms of work experience and age. In total 10 participants (aged 24 – 63,  $M = 35.4$ ,  $SD = 14.40$ ) with windstorm experience ranging from less than a year to 20 years were interviewed for this study. A total of 15 - 20 hours of data was collected through one on one interviews. The total number of windstorm surveys they had conducted ranged from one to 1,500. This

sample size was decided based on theoretical data saturation, meaning data collection was concluded when we began receiving redundant insights (Mack et al. 2005). A similar study investigating the sensemaking process of air traffic controllers recruited 11 participants (Mack et al. 2005), while a study investigating how people make sense of unfamiliar visualization recruited 13 participants (Mack et al. 2005). Further information about the participants can be found in Table 3.1.

Table 3.1. Demographic information of the participants

Variable ( $N = 10$ )	Number	%
<b>Gender</b>		
Male	8	80
Female	2	20
<b>Education</b>		
Bachelor's degree in college (4-year)	6	60
Master's degree	4	40

### *Data Collection*

Data were collected from risk engineers through semi-structured interviews following an inductive thematic approach. While the policies of the insurance company that we were working with prohibited us from going to the site to observe field inspections, a mock inspection survey was conducted on our university campus by the SME, who provided a debriefing on the specific details of the inspection process. The interview



guideline, which was subsequently designed based on the data/frame theory of sensemaking and the insights gained from the mock inspection survey, included general topics such as demographic and work experience related details. In addition, it included specific questions related to the windstorm inspection process, new technologies in use, collaboration, challenges, and the needs of the engineers. Further, a photo elicitation method was used to gather comments using visual images obtained from the SME and the Internet (Harper 2002). The images selected covered such aspects of windstorm visual inspection as roof condition, roof-top equipment and occupancy. Though the questionnaire was designed to gather insights about the sensemaking process of risk engineers, we tried not to guide our questions toward a theory. Prior to conducting interviews, the first author tested the interview guideline with the SME and made necessary changes. Additional changes were made to the interview questionnaire after telephone interviews with first few participants. Appendix B lists the interview questions used to gather data. The interviewer did not strictly follow this guideline. The interviewer had the freedom to change the questions or ask additional follow up questions based on the responses. Each of these sessions, which lasted between 90 and 120 minutes, was audio recorded. On an average, 17.5 hours of responses were gathered. The participants were not compensated for their participation.

Prior to the data collection, the participants were informed of the purpose and the potential benefits and risks of the study as well as how the data were to be used and published. All the interview recordings were de-identified using a participant number and

his/her initials. Only the first author had access to the personal and contact information of the participants. The consent form used in this study is shown in Appendix C.

### *Data Analysis*

The recorded responses were transcribed by an external agency, then checked for accuracy by the first author. The transcripts were de-identified and numbers and initials were used as a way for the first author to identify the transcripts. Coding and thematic development, one of the widely used data analytic techniques in qualitative research, was used to analyze the transcripts (Padgett 2011). This method involves identifying and coding emergent themes in the data. Unlike the grounded theory method, the end product of the coding and thematic technique will not necessarily be a theory. However, this method offers a flexible way to look at qualitative data (Mack et al. 2005). A combination of inductive and deductive coding strategies was used to code the transcripts.

The inductive coding process, led by the first author, used (Miles and Huberman 1994) as a guide for the data analysis. The first step involved the identification of open codes from the data through a line-by-line examination of the transcripts (AlMaian et al. 2015). Four researchers were assigned 3 transcripts each to identify initial descriptive codes without any preconception but keeping our research objectives in mind. The researchers identified 106 descriptive codes pertaining to risk inspection such as wind speed, roof type, guidelines, dimension and fasteners, and six attribute codes including age, gender, location, education, occupation and experience. While these codes did not have any inferential meaning beyond the respective data segment, they helped us advance to the next coding step (Punch and Oancea 2014), the development of a coding schema including the

definition of each code and a set of code rules to be followed while coding to ensure consistency.

Upon identifying the initial codes, the team members participated in an initial training exercise in which each person coded approximately 25% of one of the transcripts. The researchers were asked to label small segments using one or more codes that best explained the data. This training transcript was first individually coded, then coded as a group to facilitate discussion of individual codes in order to reach consensus. In the next step, the same procedure was used by the same researchers to code the transcript in its entirety, including recoding the section used for training. Each transcript was coded individually by two researchers, and the percentage of agreement was calculated to be 38.4% across all transcripts. However, the coders reached complete consensus after discussion. The codebook was updated to include any new codes and to combine or remove redundant or unused codes, resulting in 51 codes. During this process, the sensemaking framework was used as a guideline, meaning these new codes reflected the processes involved in the sensemaking theory such as initial cues, questioning frames and confirming frames. The new codes were then grouped into 17 family/group codes. Appendix D lists the final coding schema used for the analysis. The researchers individually coded the transcript again and reconvened to discuss their codes. Though percentage agreement across all transcripts was only 54%, 100% consensus was reached after discussion. The first author then reviewed sections at the request of the other researchers, and some sections were recoded based on the research objectives. These final coded transcripts were used for data analysis.

Each transcript was imported to ATLAS.ti qualitative data analysis software. The final consensus coding schema was used to code transcripts in ATLAS.ti. While coding the transcript, the researchers observed certain patterns among the codes, patterns that were used as the basis for applying the querying capability available in the software to identify the themes discussed in the Results Section emerging from the 51 codes. The relationship between codes and other moderating factors were also identified. For example, we investigated the relationship between experience and contradicting information to explore how experienced engineers make sense of contradictory data. While doing so, we also looked at the code cognitive skills to explore the various cognitive skills used to make sense of this contradicting information. Alternate relationships were considered among the codes and code groups to minimize the chance of not capturing possible relationships. Upon completing the report, the SME reviewed it to ensure and validate the correctness of the final conclusions. This process is illustrated in Figure 3.2.

## **RESULTS**

Using the interview responses, a cognitive task analysis was conducted to analyze the steps involved in windstorm risk inspection survey, the results being reported in Table 3.2. Then the authors applied the data/frame theory of sensemaking to determine the sensemaking process of risk engineers while conducting the risk inspection task, subsequently finding the themes of decision making based on contradicting information, role played by the experience level of the engineers while making judgement calls, factors influencing decision making, challenges faced by risk engineers and potential technology interventions. Though the results are mainly explained using roof inspection examples, the

windstorm risk inspection process is not just limited to roof inspection. Table 3.2 illustrates the detailed list of tasks involved in windstorm risk inspection survey.

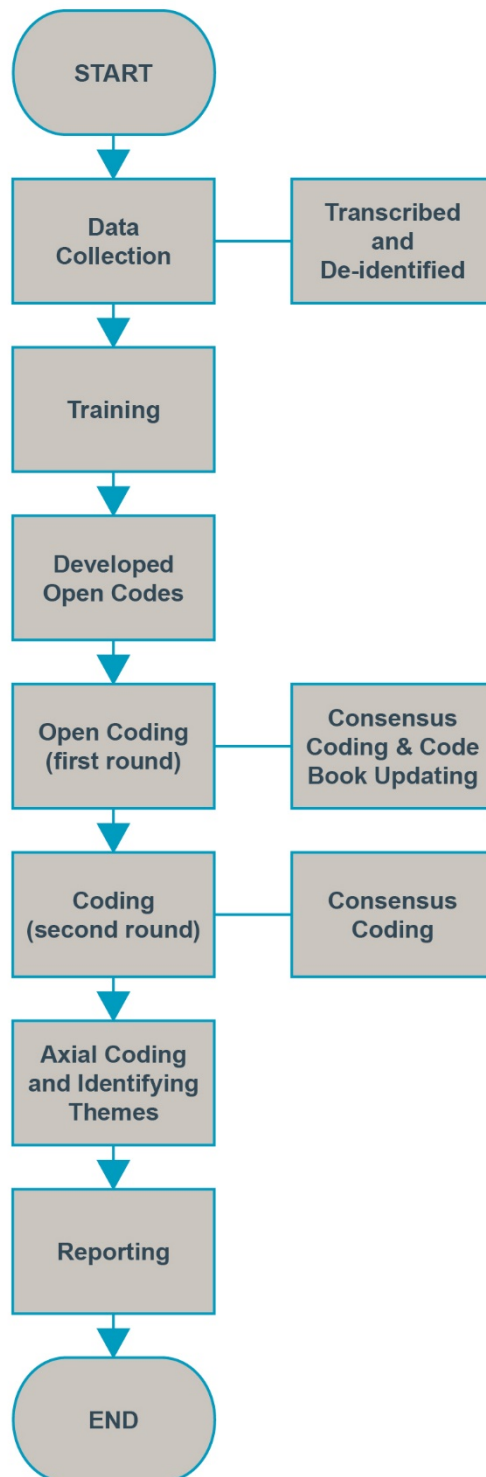


Figure 3.2. Data analysis process

Table 3.2. Cognitive Task Analysis

Task	Task knowledge/requirement	Potential problem	Potential risk	Cognitive process
1.0 Wind velocity				
1.1 Obtain wind velocity from wind data sheet		Do not know how to interpret wind data	Missile impact	Judgement Analysis
2.0 Landscaping/environment				
2.1 Look for possible missiles	Relate wind speed and missile impact (working memory)	Failed to relate wind speed and missiles Not assessed properly	Missile impact Flood	Inference Judgement
3.0 Identify building envelop construction				
3.1 Roof	Identify roof type (from long term memory) Identify potential damage based on	Misidentification of the roof Failed to recall the potential damage from long term memory	Roof Membrane/Type Damage	Judgement

	the type (from long term memory)	Type of material not available		
	Observe positive and negative factors (cracks, bubbles, parapets)	Wrong call based on positive and negative features Failure to obtain necessary information (attachment, details, etc.)		
3.2 Attachment	Observe how the roof is attached to the structure	Impossible to see the attachment	Roof Tear off	Judgement
	Use building drawings (if information is not available on site)	Failed to judge if it is properly attached	Roof Tear over	Assumption
	Recall from long-term memory based on past-experience	Information not available	Deck tear off	
	Assume based on past-experience	Poor judgment in the absence of data	Deck tear over	
		Availability heuristic (bias)		
3.3 Walls	Observe general condition of the wall (attention)	Attachment not seen Lack of information	Missile impact Puncturing	Judgement Inference



Type of the wall      Poor judgment in the absence  
(recall from long      of data  
term memory)      Overlooking wall condition  
Attachment      (inattentive blindness)  
(properly  
attached to the  
structure)\_type  
of attachment if  
seen properly,  
else building  
drawings or  
assume  
Take  
measurement  
Calculate  
pressure  
resistance  
(decision making  
based on  
guideline and  
past knowledge)  
Use guidelines

3.4 Windows	Observe general condition (attention)	Overlooking wall condition (inattentive blindness)	Missile impact Potential to be destroyed (pressure, seals)	Judgement Prediction
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	<p>Read the manufacture label (not available—drawing or assume)</p> <p>Predict the risk based on the wind velocity, dimensions and property of material (working and long-term memory)</p> <p>Take dimensions</p>	<p>Poor decision making (Not utilizing assumptions correctly)</p>	<p>allowing water to enter</p>	
3.5 Dock doors/large doors	<p>Observe general condition (attention)</p> <p>Read the manufacture label (not available—drawing or assume)</p>	<p>Overlooking wall condition (inattentive blindness)</p> <p>Poor decision making</p>	<p>Missile impact</p> <p>Potential to tear/be destroyed allowing water to enter</p>	<p>Judgement</p> <p>Prediction</p>

Predict the risk based on the wind velocity, dimensions and property of material (working and long-term memory)

Take dimensions

3.6 Rooftop equipment	Observe general condition of the roof equipment (attention) How is it attached to the roof (predict the risk based on the attachment method)	Overlooking the equipment condition (inattentive blindness) Poor judgement in the absence of adequate data	Potential missiles Potential to rip the roof membrane and deck allowing water to enter	Judgement Inference
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3.7 Occupancy & construction

3.7.1 Occupancy	Observe the machinery, stock	Poor decision making based on the occupancy	Water/wind damage	Judgement Inference
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	and supplies and finished storage	Unable to assess the value of the items/items description	Based on occupancy, storage, equipment, etc., damage could be higher or lower	
	Decide high hazard or light hazard based on occupancy	unavailable - poor judgement		
3.7.2 construction			Water or wind damage	
3.8 Emergency response plan	Observe pre and post storm activities	Failed to factor in other negative factors	Potential damage in the absence of emergency preparedness plans	
	Relate it to other existing information to evaluate its effectiveness			
	Pay attention to negative factors such as island and remote locations			
4.0 Post survey activities				
4.1 Analyze building construction	Calculate pressure resistance (Is it	Poor judgement Do not know how to use the guideline		Analysis

actually pressure resistance?)  
 Do not know the calculation/do not know where to plug in data in the software  
 Make inferences based on the information available in the guideline and long term memory (long term and working memory)  
 Do not know how to interpret the results  
 Expectancy (know where to find information in the guideline)  
 Knows how to use the guidelines

4.2 Develop recommendations	Check the feasibility of recommendations	Proposed infeasible recommendations (cost wise) Poor judgment Poor decision making	Unnecessary cost	Analysis Judgement
	Analytical skill			

4.3 Loss	Assess wind loss	Not calculated properly, not	Under or over	Analysis
expectancy	expectancy now	using guidelines properly	calculate the loss	
development	Assess wind loss		expectancies	
	expectancy if			
	recommendation			
	s addressed			
	Analytic skills			
	Math skills			

### *Sensemaking Process of Risk Engineers*

As in any sensemaking process, the windstorm risk inspection process begins with seeking information to find an anchor for developing useful frames. This process begins before the engineers physically go to the site to collect data. Building codes and ASTM standards concerning wind specific information are used to identify the wind zone requirements and wind speeds for the specific location being inspected. In addition, the clients are contacted to obtain general information about the site such as the type of the facility, its operations and its occupancy. Below are some of the comments by the engineers about the pre-survey process:

*“Let's see, it [inspection process] is partly done by researching ahead of time, one of the things we do well is obviously before we go out there is simply just try to understand what we are actually looking at, what is the occupancy but also what is [sic], how many buildings there are, and where does it change between a day's of construction as such.”*

A Google map is used to obtain the building dimensions, site condition and surface roughness. One of the participants pointed out how they use Google to support the pre-survey activities:

*“Google App might just be like the starting point, to just give an idea of what to expect.”*

The objective of this pre-survey activity is both to obtain a general understanding of the site being inspected to form the initial anchor or perception and to aid the engineers in planning the risk inspection strategy. For example, based on the information collected from Google images on the type of the roof, they decide the initial type and number of dimensions need to collect.

This anchor or initial frame is elaborated based on the new information collected during the site visit. The inspection involves a visual inspection for collecting both quantitative and qualitative information as well as reviewing documentations such as building drawings and manufacturing information, which they access when they visit the site. The quantitative information obtained includes the physical dimensions of the roof, the building envelope (windows and doors) and the fasteners to verify the information obtained from Google and building drawings. The physical dimensions of the roof and envelop are parameters affecting wind resistance, a quantitative measure of interest to risk engineers. A safety factor, a measure of wind resistance based on the dimensions, is calculated, as one engineer explained:

*“I’ll go through and make measurements to follow up on that and to verify what they have on the blueprint is the same thing that is actually finding at the building itself”*

As another participant commented on collecting more information to elaborate their initial frames:

*“It’s kind of on the fly because when you are out on the field, there are instances where you are unable to determine ahead of time which means you’d be looking at whether you have to do the analysis or you’re just handling something differently.”*

And a third emphasized the importance of this step in the process:

*“You have to get as much information as you possibly can on what is there to keep from making a biased decision like that and just running past real quick, moving on with something else. You need to find out for sure what’s there as possible.”*

In addition, various non-visual techniques such as knocking on materials, jumping on the roof, applying force on structures by pushing and pulling, and dragging a foot across the rooftop are also used to elaborate the frames. As one participant explained:

*“When I’m checking flashing, I will actually pull on it to see how well it’s secured, if it’s sealed. I’ll push my foot along, if I’m not sure if it’s a PTO roof and it’s mechanically fastened or fully adhered, I’ll rub my foot along there to see how the material reacts to that. There’s some little things like that that can be done that I will use.”*



The new information gathered during the site visit either corroborates or contradicts their expectations or mental model. For example, if the physical dimension contradicts the Google map or the building drawings, or the fasteners are not well secured, the data are challenged, and the questioning process begins. To continue using our example of roof dimensions, if the roof dimensions such as fastener spacings and envelope dimensions are acceptable, the questioning process is initiated by the detection of damage on rooftop. While questioning the frame, the engineers gather qualitative information about the site to further challenge the frame. This process of questioning and reframing is a recursive one involving continuous data collection. When the engineers encounter an anomaly such as stagnant water on rooftop that could be caused by various factors such as an incorrect slope, a clogged drain or a leaking pipe, they begin comparing these new alternative frames:

*“[Ponding could be due to] drain but also the slope of the roof so that is just from installation. You have to see that [sic] the edge of the roof and not just the middle. I don't know. It could also be a leaky pipe or a leaking AC unit.”*

This process of considering alternative causes for pooling on rooftop is further exemplified by a second engineer who comments that

*“Well, mostly from experience. I would say that I've seen a lot of ponding and most of the time, it's because of there's a blocked drain. There's grass, there's weeds. And then some other times, it's just because basically that the roof's slope is just bad but there's -- the drainage is not existent. There's really no drainage at all.”*

Though in these two comments, the process of elaboration and questioning of the frames appears to be linear, these two processes can happen simultaneously as well. During the elaborating process the engineers may encounter contradictory information that results in questioning the information and reframing. Based on the information collected, the frame will be either preserved or rejected, leading to the process of reframing. Though we explained the entire framing and reframing process using the scenario pertaining to roof, the engineers evaluate other aspects of the site using the same approach. The sensemaking process involved during various stages of windstorm risk inspection task is illustrated in Figure 3.3.

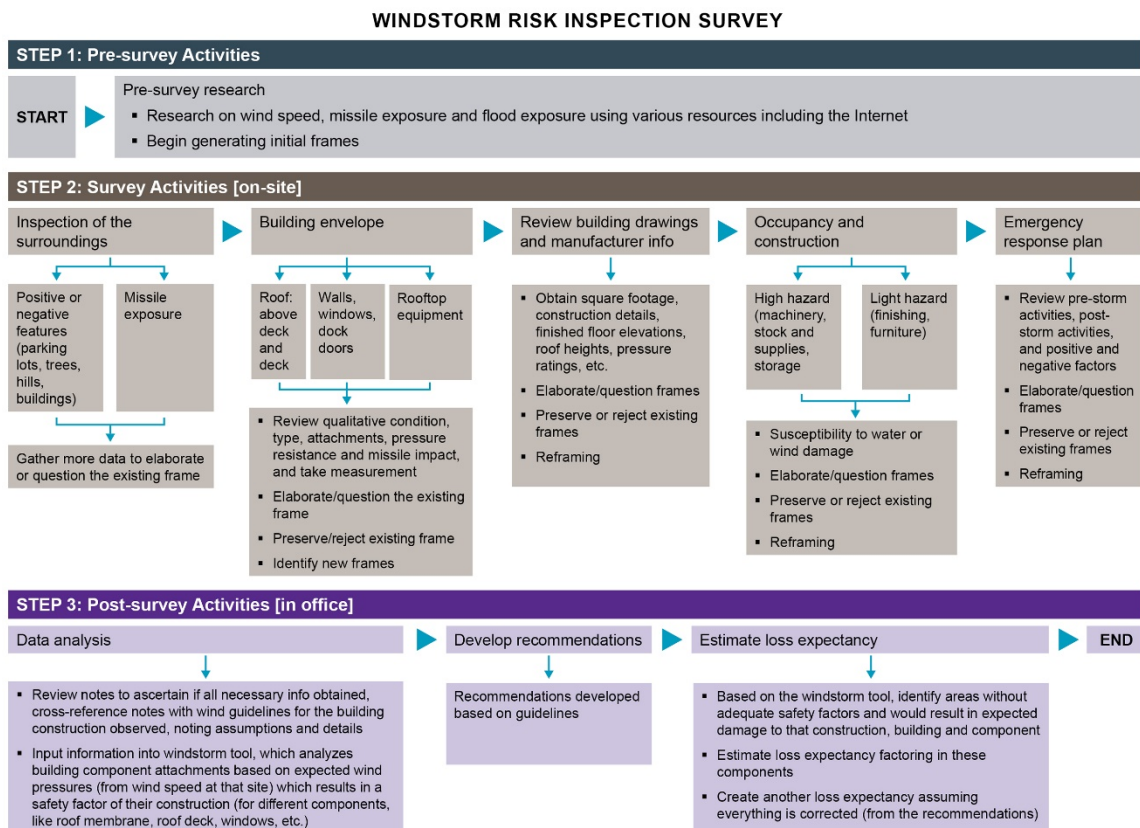


Figure 3.3. Sensemaking process involved in windstorm risk inspection survey

### *Making Decisions Based on Contradicting Information*

When making sense of the information, engineers often encounter situations in which various pieces of information contradict one another. Risk engineers referred to these contradictory pieces of information as positive and negative factors. When making sense of these factors, they consider other factors in their guidelines such as wind information, building occupancy and location, and wind exposure. When the interviewer asked them how they made sense of positive and negative factors using the example of a safety factor calculated based on roof dimensions contradicting the qualitative appearance of the roof, we observed a difference in the sensemaking process of the engineers. Some participants seemed to be conservative, basing their frames on the negative factors, ultimately preserving their frame that the roof condition was bad without questioning or elaborating it:

*“The fact that we get on this roof and it looks bad, it looks poor. That would override our safety factor said it's adequate.”*

This conservative is supported by a second participant's assessment:

*“I tend to be more conservative. I would lean towards the one that's showing that it's inadequate and have them--”*

The observation about making conservative decisions is again supported by the following comment:

*“The fact that we get on this roof and it looks bad, it looks poor. That would override our wind tool said it's adequate. Going to seeing how it's in poor condition, that would nullify the other part of information we would have for*

*the right-- I would-- even on paper it said it was adequate, the roof was sound. We even look it up here with all these issues with the water and the delamination. I will still make a recommendation.”*

However, some participants tried to gather more data to further analyze the situation, thus questioning their initial frame to identify if one factor outweighs the other. The process of weighing quantitative safety factors with a qualitative roof condition is exemplified in the comment below:

*“In certain cases, depending on what is positive and what is negative, one will outweigh the other but that just depends.”*

Their process of outweighing one factor over the other is further explained in this comment:

*“The [acceptable safety factor] is 1.3 so let's say if I do my calculations based on the quantitative information and I make -- and the safety factor is something like four or something like that, then the quality of the roof is really not that much of a factor. And so if 1.31 or it's just barely passing something like that but I know it is a bad roof, then I would lower it down and then make a recommendation”*

Some engineers even recommended further testing to determine the condition of the roof before confirming their frames:

*“I think, let's just say if 20% of the roof needs to be damaged in order to justify replacing the entire roof and so I would do some type of uplift testing or recommend a moisture barrier test. If the client says, "No, our roof is*

*completely fine," but I did see signs of damage, I would say, "You need to reevaluate that and get that approved by a certified roof inspector."”*

Another example of a situation in which the engineers may have to make sense of contradicting information is the resurvey. When engineers return to a site for a resurvey, they have access to the previous inspection report. If the information in the report supports the current site condition, their anchor frame based on the past report will be elaborated and the frame will then be confirmed. One engineer explained this situation, saying

*“Yeah, yeah. You always look at everything and you are just trying to confirm that all the rest of the report is fine.*

In the comment below, another engineer more fully explains the process of conducting a resurvey to confirm the recommendations in the past report:

*I would go in and ask first of all, has anything changed since I was here last. If they say 'yes', we focus more on those areas, if they say 'no', then it's a much general quicker walkthrough and focusing on the recommendations that were made in the past to see if a compliance was made.*

As these comments suggest, this engineer focuses on changes that were made since the previous inspection.

However, if the pre-survey report contradicts the current site condition, the questioning process initiates and the engineers investigate the reason behind this disparity. Based on the information collected from the site, the frame is updated or a new frame is developed. The following comment explains the engineers' questioning process if there have been any changes since the last inspection:

*“You could have 10% of the roof from some outer edge that was compromised and we can check the old report and say, “Okay, yes. The corner of the east-most building safety factors were not adequate. But that was not actually the one that failed so let's figure out what's going on with the tool. Is this just a fluke? What's going on?””*

In this situation, the engineers investigate the site again to detect any further damages or information that is not mentioned in the previous inspection report:

*“Yeah, yeah. You always look at everything and you are just trying to confirm that all the rest of the report is fine. If something looks different or anything like that [sic] but yeah you just want to confirm that everything is okay and then the other thing, we look at the roof if it's [worse] than last year, it's getting deteriorated and things like that. But yeah it's more like a confirming [sic] and putting it again in the report.”*

Without further questioning and elaborating the initial frame, there is a chance engineers may make biased decisions when faced with contradicting information. To avoid this situation, they use their judgement skills while elaborating, questioning, reframing and confirming the frames as they weigh various factors associated with contradicting pieces of information.

#### *Effect of Engineers' Experience Level while Making Judgement Calls*

Though the engineers complete the inspection process following a standard protocol, their sensemaking process varies depending on their experience level. The experience level of the engineers interviewed in this study ranged from under a year to 27 years, with a few of

them having completed hundreds of risk inspection surveys. Since each inspection site is unique, no two buildings probably have the same roof or structural features, meaning even experienced engineers sometimes encounter unexpected situations as the participant comment below indicates:

*“That's one of the issues with wind there's a lot of variables and so I think I'm really comfortable like I am with certain roofs, and they might be very common roofs as well, but then I could still look at a site and have no idea what I'm looking at possibly.”*

Though this engineer is experienced and comfortable with a variety of roof types and structural features, he/she still encounters unfamiliar structures; however, experienced engineers are better equipped to deal with such situations.

When dealing with an unfamiliar or even a familiar situation, engineers have to make judgement calls based on the experience they have gained through their work on previous sites. For example, according to an experienced engineer, there is no set rule in the guidelines that helps the engineers assign relative weights to various positive and negative factors in this process. He concluded saying:

*“At the end of the day, it's a judgment call but all those factors should weigh into the engineer's mind as to how much credit to give something. Like I said, it's never a perfect science but the more you can narrow that distribution curve, the better your assessment is going to be.”*

A second experienced engineer explained this process of assigning weights to positive and negative factors this way:

*“With our guidelines we get some that are lifted out, which ones you should consider positive or negative factors. But there's no real science in terms of how much credit you might give them. That comes down to as we want to go through with engineering judgment whereas you have to make a judgment call yourself.”*

Although as this engineer indicates the process is not a perfect science, it becomes easier as the judgement calls become more accurate with the experience:

*“But the biggest thing is experience over time, giving different weights to different things and knowing the values of some. And learning how -- from loss lessons how to make those judgments.”*

As a result, the experienced engineers can consider multiple alternate frames before finalizing one and coming to a conclusion that incorporates information both from the guidelines and their experience level. As one engineer explains, their judgement is the most important skill when trying to make a fuller frame based on limited information:

*“We need to have certain engineering judgment and just the cause in determining what should we assume for this type of situation because you don't have any information otherwise to go to.”*

*“Being able to know the picture of something that honestly, you're probably not going to get clear-cut data for so just inferring the data from what you can see and what you've learned from the client. You really got to build your own image and piece together the puzzle from very limited known data and*



*you've got to make a lot of decisions without knowing exactly what the answer truly is.”*

As these responses suggest, experienced engineers develop a mental model/hypothesis as accurately as they can based on their experience and their observations. Then before arriving at a conclusion, they consider alternative frames to identify potential causes for any damages they observe. Thus, they are more likely to avoid confirmation bias, the tendency to seek evidence supporting a preconceived belief or one based on limited information, than an inexperienced inspector who may not be able to question the frame or consider alternative ones.

To investigate the importance of experience further, we asked our participants about the different reasons for stagnant water on a rooftop. One of the responses is below:

*“I would say that I've seen a lot of ponding and most of the time, it's because of there's a blocked drain. There's grass, there's weeds. And then some other times, it's just because basically that the roof's slope is just bad but there's - the drainage is not existent.”*

This experienced engineer can come up with three possible reasons for stagnant water on a rooftop based on observation. However, novice engineers may not always be able to come up with alternative frames and think through the various consequences of their decisions. One engineer explained the difference between the ability of a novice and an experienced inspector in questioning a frame, saying

*“That's where it kind of separates the experts and the amateurs, because you have to really think about what are all the consequences of this. You have to*

*think through the whole thing and be able to defend your argument, because you can't fall back to a code or guideline to back you up in your decision making because it's all you."*

When thinking through various alternatives, the engineers have to defend their conclusion by thinking of the possible consequences of their decision. This assessment of experienced engineers is potentially more accurate than that of a novice even in the absence of information:

*"There are times that I have to make assumptions based off of my experience level. There's times that I cannot make measurements, and I don't have blueprints. Just from experience I'm able to make a good estimate of what something-- how far apart joints are, or how far apart, the panels are mechanically bad. There are ways to use my past experience level in recognizing what I'm seeing and making a very good estimate off of that."*

This engineer can make reasonable estimates of joint spacing and dimensions even when if he is unable to take the measurements or cannot consult blueprints.

While the diversity in site conditions, the lack of information and the tendency for confirmation bias make it difficult to complete the risk inspection process with highest accuracy, the engineers can rely on their experience level to arrive at accurate assessments. Each inspection brings a unique opportunity for risk engineers to enhance their ability to make sound judgement calls, a skill that, developed over time, plays an important role in risk engineers' sensemaking. The importance of experience was best explained by a novice engineer:

*“The more experienced guys like [name] and [name], they are going to be able to make more hypothesis, more than them-- they probably know more or less when something looks wrong. It's probably wrong, or when the maths wrong. Me, on the other hand, I don't really have a lot of experience yet, though I always have to go back and double check my numbers”*

#### *Factors Affecting Engineers' Decision Making*

While engineering judgment and experience level play a role in the domain of risk inspection, the decision making process of risk engineers also depends on various internal and external factors. We divided the most important factors influencing this process into 2 categories, internal biases and external biases; the former are those biases inherent in the risk inspection process such as the ones introduced by the use of checklists or past inspection reports, while external biases result from external factors such as weather conditions, building codes or individual differences. All of these factors impact the mental models of the engineers and, hence, their perception of information.

Both experienced and novice engineers are affected by internal biases as they are inherent to the inspection process. For example, the availability of past inspection reports for the site for they are to resurvey can influence their decision making, especially if they do not complete a full inspection because of they do not have this access or they cannot confirm the past report. One participant explained how the lack of a past inspection report can bias decision making:

*“That's one thing that could bias your report definitely. If you're really reliant on your previous information and you don't go through the process*

*of visiting all the roofs and checking that everything looks good then, yes, you could overlook something for sure.”*

Moreover, the experience level of the engineer who conducted the past inspection can influence the resurvey process. If the report was written by an experienced engineer, subsequent engineers may place a high trust in the information, a situation that could influence the thoroughness of their inspection process. However, if the engineer was a novice, the engineer conducting the resurvey would not have complete trust in the information. As one participant explained

*“One thing, you need to look who did the report. If it says a specialist did the report, I will have a bias and say that the report is good. If I knew a guy with 3 months of experience did the report, I'm going to say the report, maybe is not as good. Maybe it is good, maybe it is not”*

Even if the experienced engineer who conducted the past inspection made several errors, the engineer conducting the resurvey may not always question the earlier report, resulting in errors in the new one as well.

In addition, internal bias can also be introduced through the checklist used to ensure a complete and methodical survey as it lists all the steps required and the dimensions needed. However, our participants expressed mixed opinions about the use of checklist when asked if it biased their inspection process, with various engineers commenting on the advantages of using a checklist:

*“No, nine out of 10 times you want to say no [they don't bias it]”*

*“No, I would say that they usually help. They don't really affect my decisions, they affect my level of collection -- data collection. I don't think they bias it, I think they improve it.”*

*“No, not really. It just helps me stay on track and systematically ask questions, rather than sporadically skipping around and potentially forgetting to ask something.”*

*“No, I don't think it would bias me to miss something, or change anything. It's pretty generic. I don't think it would negatively affect the survey.”*

However, not all participants agreed that using a checklist improves their inspection process, indicating that they believed it biased their process and decision making:

*“Checklist can be good or can be bad, because if you give me a checklist, you can miss something that is not on the checklist”*

As one participant further explained:

*“It could if you're solely looking for the information that you listed and not trying to find anything else, then, yes, it could.”*

As these comments suggest, the inspection process can be constrained by the use of a checklist.

In addition to internal biases, the engineers are affected by biases introduced by external factors or inspecting engineers, for example the use of manufacturer information and building drawings. If the engineers rely on building sketches and manufacturer labels for required information rather than taking actual measurements, they may arrive at biased conclusions. Just because a manufacturer label is approved by building codes does not

mean that the structure is going to withstand extreme weather conditions as its structure under such conditions depends on various other factors discussed in this article. As one participant explained:

*“You may have building plans that say this roof is built to survive a category four hurricane here in Orlando, but then it's installed improperly.”*

Furthermore, engineers in this study discussed common misconceptions about such manufacturing labels:

*“The biggest thing is that people get the common misconception about wind rated windows. That just, because you may be in Tampa or you may be in New York or you may be in South Carolina, you can get Miami-Dade County windows. They're approved, because Miami-Dade County is one of the best windows you can buy. That's a common misconception.”*

These two comments emphasize the bias resulting from basing decisions on manufacturer labels.

Other external factors influencing the decision making process are the hypotheses/assumptions the engineers develop based on their mental models. A key factor affecting this model is the critical cues they perceive that generate their hypotheses. For example, wind speed is critical information: if the property is located in a high wind speed region, the engineers may arrive at conservative conclusions and recommendations. One participant discussed how the inspection strategy and framing process is influenced by the wind speed value:

*“We have internal guidelines depending on what the wind speed is on what exposures we have, whether it be small missile, or large missile exposure. Depending on the values of the building, will determine whether or not a basic level or an advanced level wind survey is complete.”*

An additional participant explained how the wind speed value affects the recommendation concerning fastening a structure on the rooftop:

*“It looks like there are some bolts going into the base of the structure on top of the building for this sand and bit. I would likely say yes, but it does depend on if it is at higher wind speed area. I may recommend that they have guy-wires, secured down to the structure member underneath the bed.”*

Structures in higher wind speed areas require additional securement as the wind can lift them from the rooftop, causing additional damage to both the rooftop and the neighboring buildings.

However, a number of other factors also need to be considered when making decisions based on wind speed to avoid bias. Though wind speed is pivotal in deciding missile exposure, engineers, especially the experienced ones, tend to consider other factors such as surface roughness, proximity to other loose structures, landscape and land type (whether inland or coast) as explained in the following comment:

*“When I get into where I figure out what the wind speed is, in my head I’ll kind of have an idea of if it’s going to be a really big exposure to this site or it may not be. I went to a facility, last week actually they had a 105 mile an hour wind speed and there are really no small missile impact exposure, there*

*were no storm surge though it was that hint of a exposure. Compare it if you go to do Miami or Key West.”*

As this engineer explained, other factors such as exposure and the possibility of storm surge also need to be considered. The comment below further explains how exposure affects the decision making:

*“We have surface roughness. If you have wind speed-- for example, if you're in a coastal location and you're right on the beach and you have a hurricane coming, you don't have anything to block its pressure. “*

As these engineers indicated, they are required to investigate many different factors before coming to a conclusion, these key factors helping them develop a mental model about the current site condition. This mental model will help them analyze the data and propose recommendations to improve the resilience of the structure in the event of extreme weather conditions. Since this mental model is highly subjective, the interpretation of the data based on it and engineering judgement could vary from person to person. These individual differences may result in different interpretations of the same site, impacting the consistency of the inspection and the subsequent recommendations, especially because the skills of the individual inspectors depend on their experience level. This subjectivity affects the accuracy of their findings, making it difficult to compare reports across inspection sites:

*“Everybody interprets everything differently, so I think if five people went out there, or 10 people went out there, you'd get 10 different viewpoints, and probably most of them would be very similar, but the fact is, you would have ten different viewpoints”*



As with any manual inspection task, the issues introduced by internal or external factors make the windstorm risk inspection process a subjective one.

When asked about how they would address the biases introduced by factors including, but not limited to, their expectations, manufacturer labels, building codes, guidelines and past inspection reports, the participants emphasized they try to complete the inspection process in its entirety. In addition, they are they are trained to avoid the biases introduced by these factors as they complete their inspection process, offering such strategies as:

*“I'm not sure if those approvals [wind ratings] are enough as it is. Those approvals should be-- I don't know where I'm going with that, but I will try to get more information to see how it's attached, to see if it winds up with what the navigation tool is how it should be attached.”*

Another participant advocated for the need to double check the information collected, saying

*“That's why we are there to double check and why we've got a review team. Because it's only designed as good as it's installed. That's why these placard, they may look good on paper, but at the end of the day, it's going to be completely wrong.”*

In addition to collecting further information and checking the safety of the structure even if it meets the building codes, engineers also address the biases introduced by the past inspection reports:

*“Of course, it's not that we doubt our own employees, but as engineers, it's always just good judgement to, you could actually try to verify everything yourself. If you verify everything, then of course you can-- that's great, because you can just pretty much go with what the old report because you've verified it.”*

A second engineer echoes this comment:

*“But I would say biasing, you probably either got to be a lazy engineer or naive engineer because I don't really think engineers are going to be biased based on the information they're given. Because at the end of the day, that's your entire job, writers, to write a report that's as accurate as you can”*

Though the engineers are subject to various internal and external biases, experienced engineers are better equipped to address them by confirming the information gathered with alternative frames and critically analyzing the consequences of their decision.

#### *Difficulty developing the mental model of the future state*

Difficulty in developing a mental model for the future state of an infrastructure can be attributed to two primary factors. The first factor is the information overload caused by the large amount of data collected as it is difficult to analyze all of this information to arrive at a meaningful conclusion. The second reason is that the risk inspection process involves predicting what is going to happen to the infrastructure in the future without any reference; as with all humans, the ability of engineers to foresee the future is limited.

When the inspection is completed, the engineers may have obtained a large amount of complex data from the site through images and notes, information potentially relevant

as well as irrelevant. First, the engineers have to sort through both the quantitative and qualitative data they collected from the site, followed by analyzing the information and writing the report. They use an internally developed proprietary tool referred to as wind tool to analyze the quantitative information collected to determine the load the building can safely handle. This calculation is based on such important factors as building location and age, wind information, and missile exposure, as well as several other characteristics. These various factors are triangulated to derive meaningful conclusions from the data, a challenging task for the engineers. This step requires them to apply their experience and engineering judgement to complete the mental model. Even experienced engineers agree that analyzing these data can be challenging:

*“There was just so much information they had there to look at, to evaluate for, you know, that was a 10 hour long survey”*

Novice engineers find it especially overwhelming to analyze the data and write an inspection report as seen in the following comment discussing the challenges they face:

*“I had a really rough time writing this report. It was six different roofs and I'd only ever done two of those roofing systems then it was all new, it was my fourth written report ever. It was a lot of analysis, it was pretty complicated. My experience level is very low and so I found it very difficult. It was like drinking water from a fire hydrant, it was a lot of information.”*

In addition, according to a second novice engineer, they do not get any training on writing this report, meaning they have to learn it on the job:

*“I never went through any training, aside from following along with people. So sitting down and trying to figure out how to write all of that for the first time was challenging without help from somebody that could actually sit there right next to me, and be like, “Hey, this is how you do this””.*

One of the important components of this report is the recommendations the engineers propose for the deficiencies they observed based on a feasibility criterion of 1:10 cost-benefit ratio. To compute this ratio, the engineers need to project the loss in the event of an extreme weather condition and compare it against the savings the client could realize by implementing the recommendations the engineers propose. Therefore, essentially this report is their future mental model. However, predicting the status of the infrastructure in the near future can be a challenging task for risk engineers because they seldom receive feedback on the results of their conclusions and recommendations. In addition, it is not guaranteed that the clients follow through with the recommendations the engineers make. They can check the accuracy of their report only when they conduct a post-catastrophic loss investigation process, comparing their future mental model with the actual result from an event and, based on this comparison, updating the inspection process and guidelines as needed. However, they rarely are able to make this comparison because neither hurricanes nor tornadoes are frequent occurrences. Moreover, for novice engineers with limited risk inspection experience, developing this future mental model is challenging as the ability to predict the future of the system, an important skill for risk engineers, requires being able to critically analyze the current status and to propose recommendations.

*Potential technology interventions*

One potential way to achieve an accurate prediction without a catastrophe is to incorporate technical visualization strategies to help the engineers predict the future of the infrastructure. Currently, although risk engineers do not use a technological interventions extensively, one potential strategy is the use of 3D immersive simulations to help with these predictions. Such virtual technologies have been used in various civil engineering applications to visualize site information (Atherinis et al. 2017). For example, Jáuregui et al. (2005) explored the possibility of virtual reality in a bridge inspection application, using a QuickTime Virtual Reality system to aid inspectors in reviewing the condition of the bridge as if they were at the site. The potential of such systems in the domain of risk inspection could be explored. Although it would be impossible to physically feel, knock on, or pull the structure, engineers could observe things more closely and safely in a 3-D environment.

In addition, such virtual environments avoid the need for physically accessing the roof, a difficulty all of our participants reported facing. When asked about using technologies to address this issue, they responded

*“Now, we have the drone capabilities, so even if it's not safe for us to physically get on the roof, if you're drone certified and not in a restricted airspace, you could always fly the drone up and get pictures that way as well.”*

The ability of drones to supply these pictures was supported by another participant:

*“Some people have been trained in flying drones. We're able to take pictures that way.”*

A third participant focused on the fuller perspective that this technology makes possible:

*“Well, it can give us different viewpoint, and that's probably the biggest needs, different viewpoint and allows you to-- I mean, in theory, it could potentially-- if we could get like drones in particular, to the point where we wouldn't go up on roofs, it could save the time of going up there yourselves. I know they have very high-quality cameras on them but you have to be careful about how you observe things through the drone and make sure to get all the correct information.”*

As these comments suggest, our participants viewed unmanned aerial vehicles (UAVs) or drones as a convenient tool that can be used in windstorm risk inspection, one that enhanced the safety of as well as the information obtained during the process.

Although promising, several factors limit the use of drones in risk inspection including unfavorable weather conditions, air space restrictions and the lack of skilled operators. In addition, it is difficult to obtain accurate dimensions when using a drone for data collection. Currently, image stitching algorithms are used to obtain dimensions from the images taken by UAVs. However, the results of this method may not be as accurate as taking physical dimensions. The engineers hope to augment drones with infrared and thermal imaging techniques in the future to collect detailed information about the inspection site. These techniques would help the engineers detect the presence of moisture on rooftop and observe different layers of the roof. Moreover, various computer vision techniques can be used to accurately predict the state of the current system by potentially minimizing the subjectivity associated with the manual inspection procedures.

## DISCUSSION

The results of this qualitative research have demonstrated that the sensemaking process of the risk engineers is complex due to a variety of factors ranging from the experience level of the engineers to the environmental conditions. Humans tend to generalize data gathered from non-representative sample (Khasawneh & Ponathil, 2018; Ponathil et al., 2017). Experience is an important factor that prompts engineers question their data to ensure they are addressing any biases. Each inspection survey has been a learning experience for them, serving as an opportunity to expand their knowledge of roof types, occupancy and missile exposure. The risk inspection process requires the generation of hypotheses and questioning to test their accuracy of their information and knowledge. The very nature of this job makes any technological interventions that provide the users with several alternative hypotheses futile (Klein, Moon, & Hoffman, 2006a) because such technologies would inhibit risk engineers from elaborating and questioning their frames. However, it would be beneficial to develop systems that assist framing and reframing by making data collection easier. For example, for inspecting inaccessible areas of a property, a mixed reality system could be developed to simulate the real-world condition. Such a system would help engineers by guiding their sensemaking process and by avoiding the need for drawing conclusions solely based on guidelines. Furthermore, such intelligent systems could assist novices by guiding their sensemaking process.

When elaborating frames, comparing alternative ones is an important skill for a risk engineer. However, novice engineers may not always consider all potential alternative frames because of issues in developing accurate mental models. For example, water

pooling on the rooftop could be caused by a variety of reasons ranging from rain to an improper slope. However, a novice engineer may fail to consider all reasons when critically analyzing the situation. An automated system could help such engineers by guiding them through the sensemaking process. Furthermore, such systems could help address biases and errors by assisting engineers in critically analyzing each of the reasons and factors impacting a certain condition. Although such systems can equip engineers with the assistance to improve their sensemaking process, their own skills for engaging the sensemaking process are critical. Training scenarios need to be developed to improve the overall sensemaking skills of risk engineers for critically analyzing a situation.

Klein, Moon, & Hoffman (2006b) asserted that intelligent systems would help people make sense of information rather than merely assisting them as such systems can synthesize data in meaningful ways to provide insights to the users. Risk engineers can benefit from these systems by making use of those succinct and meaningful insights while performing inspection surveys. It is not uncommon for these engineers to feel overwhelmed by the amount of information available to them when conducting a risk inspection; thus, it is possible that they could overlook important data because of a high signal to noise ratio. This bias could be minimized by the introduction of intelligent systems. According to Klein et al. Klein et al. (2006b), reasoning bias rather than confirmation bias could lead to inaccurate decision making. Intelligent systems can help users address such biases by encouraging them to consider alternative hypotheses when the existing hypotheses may be inaccurate (Klein et al., 2006a). Such systems can assist risk engineers by giving them confidence in their decision, whether it is to keep their existing frame or to reject it to



consider alternative frames. However, novice engineers need to be trained to avoid bias resulting from the inaccurate predictions made by intelligent systems (Klein et al., 2006a).

Although these automated systems can assist the risk engineers or any infrastructure inspectors when conducting inspection tasks, such systems, according to Endsley & Kiris (1995b), have the potential to eliminate the inspector from the loop. As some of the tasks will be conducted by automation without human intervention, the SA of the operator will be degraded, affecting his/her performance (Cummings, 2004b). SA involves the perception of elements in the environment (level 1), the comprehension of these elements (level 2) and the projection of the current system of these elements and the environment into the near future (level 3) (Endsley, 1995b). This concept of SA is important in the context of risk inspection or civil infrastructure inspection in general. In the domain of infrastructure inspection, level 1 SA involves perceiving various elements in the environment such as ponding on a rooftop, a cracked or bubbled roof, elements in the surroundings and various objects inside the building. Level 2 SA involves comprehending these elements and understanding their status and that of the system. As it involves understanding the reason for the collection of water on the rooftop or the bubbled roof, for example, Level 2 SA is crucial for diagnosing issues and proposing possible recommendations to fix them. Level 3 SA involves predicting how these issues affect the functioning of the infrastructure in the future or in the event of an extreme weather condition (Endsley & Robertson, 2000).

Predicting the effect of various issues in the near future can be a challenging task for infrastructure engineers, especially for novice engineers, because they lack the

experience to be able to see what could happen to the infrastructure in the future or in the event of an extreme weather condition. Other reasons affecting the ability to achieve SA include forgetting to collect the required information, skipping important steps, overlooking critical cues, and neglecting to consider alternative frames (confirmation bias) (Endsley & Robertson, 2000). These factors need to be considered when designing intelligent systems to support infrastructure inspection. By considering these factors, visualization strategies can be developed to help support engineers achieve sufficient SA to complete the inspection task successfully. Furthermore, training programs can be developed, especially for novice engineers, to help them avoid various biases while achieving SA.

To support the SA requirements, it is important to make critical cues salient and to provide Level 1 and 2 SA information directly (Endsley, 2016). In order to cue engineers to perform the necessary tasks and to support their SA requirements, the authors developed a checklist based on the findings from this study (Appendix E). As explained in the Result section, one of the reasons for the inconsistency in the risk inspection process is the lack of a standard protocol. This checklist includes step by step instruction for carrying out windstorm risk inspection process. Upon developing this checklist, it was reviewed by the SME. The checklist was then updated to include the suggestions proposed by the SME. Additional field testing is required to validate the checklist by risk engineers while carrying out windstorm risk inspection survey.

Though this research studied and identified the sensemaking process of risk engineers, this research is not without limitations. The authors interviewed engineers from

only one organization. So, the generalizability of the findings from this research is limited. In addition, only 10 engineers were interviewed. Though the authors achieved data saturation with 10 participants, more engineers from multiple organizations need to be interviewed to improve the generalizability of the findings. Additionally, conclusions were drawn solely based on the interview responses. Observational studies need to be carried out to investigate how risk engineers carry out the risk inspection task in the real-world. Furthermore, the checklist developed needs to be field tested to ensure the validity of its content.

## **CONCLUSION**

The objective of this interview-based exploratory qualitative research was to explore the sensemaking process of windstorm risk engineers. More specifically, our goals were to examine the various steps involved in windstorm risk inspection, the sensemaking and mental model development process of the engineers, the factors influencing or biasing this process, the difference between novice and expert engineers while making sense of the information, the challenges faced by windstorm engineers and the potential for technology intervention. The findings from the detailed qualitative research protocol based on an inductive thematic method used in this study to address these goals suggest the need for automating the risk inspection process to minimize biases and subjectivity. Furthermore, these results can be used to develop training modules to help engineers, especially the novices, achieve SA while conducting risk inspection activities.

The findings from this research can inform the design of training programs and technological interventions. The fuller understanding of the risk engineers' sensemaking

strategy in the physical world obtained through this study will help design immersive systems assisting them during the inspection process. Our next step will be to develop immersive automated systems assisting the sensemaking process by providing engineers the SA required. Furthermore, it is important to investigate how new technologies like drones, infrared imageries and virtual reality are perceived by the engineers as aids to assist them in their risk inspection process. There is a need to conduct further empirical research evaluating the effectiveness of using these and other technologies in the windstorm risk inspection process. In addition, more studies need to be conducted investigating the possibility of converting the qualitative information collected during the risk inspection process to quantitative information to develop predictive models that facilitate informed decision making.

## CHAPTER FOUR

### AN EMPIRICAL STUDY TO INVESTIGATE THE EFFECTIVENESS OF CONTEST-BASED VISUAL DECISION AIDS TO IMPROVE THE SITUATION AWARENESS OF WINDSTORM RISK ENGINEERS

#### INTRODUCTION

Over the past ten years, an average of 170 wind-related fatalities were reported in the United States annually every year (“NWS Analyze, Forecast and Support Office,” 2018). Such wind-related natural disasters as hurricanes, tornado and thunderstorm affect individuals and society as well as the economy (Tokgoz, 2012). The effect of these disasters range from direct damages such as physical destruction and damages to assets and capital to the resulting indirect damages (Khazai, Merz, Schulz, & Borst, 2013). Property damage is one of the most important consequences of natural disasters, costing billions of dollars in losses (Fernández, 2001). In 2017 only such weather events resulted in a cumulative cost of \$306.2 billion (“Hurricane Costs,” 2019). To limit the extent of these damages, wind vulnerability assessments are conducted to identify and mitigate damage and to minimize disruption (Smith, 2011), and insurance companies conduct routine inspection tasks or loss prevention surveys in their clients’ facility to reduce the frequency and severity of such damages (Schlesinger & Venezian, 1986). Though this process, known as a windstorm loss prevention survey or risk inspection (What is the Windstorm Inspection Program?, 1999), can benefit both the clients and insurance company, the accuracy of the findings depends on the skillsets of the engineers conducting the inspection (Agnisarman, Khasawneh, Ponathil, Lopes, & Madathil, 2018).

Previous research investigating the sensemaking process and situation awareness of windstorm risk engineers identified the lack of a standardized survey protocol as one reason for the disparity in their findings. Furthermore, individual differences in the ability and experience level of these engineers contribute to this subjectivity (Agnisarman et al., 2018), with the latter being one of the most important factors contributing to the accuracy of the inspection report. Experienced engineers can develop a more accurate mental model about the current state and the future state of the infrastructure than their novice counterparts who, due to their lack of experience, may find it challenging to perceive and comprehend information to develop an accurate mental model of the infrastructure system (Agnisarman et al., 2018).

Automation-assisted technologies and Artificial Intelligence (AI) have been used by researchers and practitioners to improve the accuracy of the infrastructure inspection process (Agnisarman, Lopes, Chalil Madathil, Piratla, & Gramopadhye, 2019). AI algorithms can facilitate decision making by reducing the mental demand on the risk engineers by assisting them with the preliminary data analysis and cue the engineers to look for relevant information when completing the risk inspection task. However, such technologies are not without limitations. These technologies can assist in conducting infrastructure inspection, the engineers' ability to interpret and make sense of the data is important (Agnisarman et al., 2018), especially since operator performance in such systems is mediated by vigilance decrements, complacency and loss of situation awareness (M. Endsley, 1999; M. Endsley & Kiris, 1995).

Artificial intelligence based algorithms have been used extensively in the domain of infrastructure inspection (Lu, Chen, & Zheng, 2012; Naser & Kodur, 2018; Sousa, Matos, & Matias, 2014), for example in expert systems, knowledge base systems, intelligent database systems, and intelligent robot systems (Lu et al., 2012). Traditional intelligent systems are siloed and confined to one specific domain. However, in this era of distributed intelligence, there is a need for the individual systems to interact with one another and operate across multiple domains (Pentland, 2017). In addition, various issues such as poor performance and lack of transparency may result in distrust in intelligent systems (Pentland, 2017). However, over reliance and complacency can result in misuse of the system. More specifically, in highly automated systems, handoffs between human users and automation can be challenging (Guszcza, 2018), an issue that can be mitigated by using a human-centered design process to ensure this transition process is smooth and seamless.

In the risk inspection domain, AI is not expected to completely automate the risk inspection process. Instead, it can augment the risk engineers' decision making with the help of predictive algorithms, which generally outperform expert judgement as risk engineers' ability to predict what will happen in the event of an extreme weather condition is limited. However, human involvement is required to make decisions about unusual situations that are not accurately modeled using historical data (Guszcza, 2018). Such situations require intelligent systems to generate anchor points for the experts to augment human decision making (Guszcza, 2018). To support this effort, there is a need to develop algorithms meeting contextual needs. The human-centered design should highlight

the needs and requirements of the specific context under consideration to facilitate the optimal use of AI algorithms, emphasizing the importance of considering situation awareness in designing decision aids based on AI for risk engineers (Agnisarman et al., 2018).

### *Situation Awareness*

Situation awareness is the perception of the elements/cues in the environment (Level 1), comprehension of the current situation of the elements (Level 2) and the projection of the status of the elements and environment in the future (Level 3) (Endsley, 1995). Any of these levels can be affected by automated systems that keep humans out-of-the-loop, a consequence of automation analyzed in early studies on human-automation interaction (Endsley & Kiris, 1995). This SA theory proposed by Endsley (1995) has been widely used in such domains as aviation, aircraft maintenance and surgery in an effort to improve operator performance (Endsley & Robertson, 2000; Fioratou, Flin, Glavin, & Patey, 2010; Jones & Endsley, 1996). However, our systematic literature search did not retrieve any articles in the domain of loss prevention inspection or infrastructure inspection investigating the situation awareness (SA) requirements of inspectors/engineers. To address this lack of research, this study focuses on designing context-based visualization strategies to improve the SA of infrastructure/risk engineers.

### *Relevance of SA in infrastructure risk inspection*

Infrastructure risk inspection process involves identifying wind vulnerabilities associated with a building to reduce the extent of damage in the event of extreme weather conditions. Though SA has been used extensively in the context of dynamic systems, this



concept is relevant to the inspection and maintenance domain as well (Endsley & Robertson, 2000). Though the infrastructure inspection process does not involve a dynamic environment, risk engineers need to develop a mental model of the future state of an infrastructure based on its current state. However, there are a number of unknown factors such as wind speed and direction, the overall condition of the infrastructure, and other interdependencies such as the distance between missiles and infrastructure system and locations of other objects that make predicting the future state of the infrastructure a challenging task. More importantly, the dynamic events and behavior patterns of the components of an infrastructure following a higher category hurricane pose a real challenge for the risk engineers.

The Level 1 SA requirements of risk inspection involve perceiving cues including, but not limited to, the type of roof, type of rooftop equipment, age of the roof, surface roughness and missile exposure. In Level 2 SA, the engineers comprehend the information perceived, creating a mental model of the current state of the infrastructure. During this process, engineers may face a number of challenges, the most important one being the lack of information available. Level 3 SA requirements involve predicting the future state of the infrastructure in the event of extreme weather conditions based on its current state. The sensemaking process of infrastructure risk engineers during this process has been discussed in detail in another article (Agnisarman et al., 2018). While AI-based automated systems are used to support the windstorm risk inspection process, there is a need to understand how engineer's SA is impacted. In this research we will develop information visualization strategies to support the SA requirements of the windstorm risk engineers.

### *Risk assessment*

There are 2 primary methods currently being used for assessing hurricane structural damages: the subjective method and the analytical method (Mehta, Smith, & McDonald, 1981). The subjective method involves windstorm engineers going to a site to obtain information about the roofing system, envelope, connections, drawings and specifications, while the analytical method is based on the principles of structural mechanics and an understanding of material properties to predict wind speed and potential damages (Mehta et al., 1981). The subjective windstorm visual inspection method detailed in Chapter 3 formed the basis for identifying the information needed in the visualizations. In addition, analytical hurricane damage prediction models were also explored to identify the elements that need to be included in the contextual visualization.

Risk involves both the probability of risk realization and the effect of threat realization (Väisänen, Noponen, Latvala, & Kuusijärvi, 2018). Though human visual perception is capable of detecting anomalies and patterns, the ability of the risk engineers to predict the future state of an infrastructure is limited. Information visualization uses external aids such as computers to strengthen the cognitive capabilities of users/decision makers (Kapler & Wright, 2005). Risk visualization, which involves visualizing potential risks to enhance cognition to facilitate decision making, will potentially augment the inspector's cognition and enhance his/her situation awareness. However, presenting the specific data needed to meet the demands of the end user can be challenging since it involves identifying the visualization requirements of that user group (Kasireddy, Ergan, Akinci, & Gulgec, 2015).

### *Related works*

The design of technologies to support SA has been investigated extensively in aviation and healthcare. Additionally, the SA theory proposed by Endsley (1995) has been used to investigate the effect of various types of display strategies, specifically tactical vs. waterfall, for submarine track management in a simulated environment (Loft et al., 2015). This study investigated the relationship between various SA measures such as Situation Present Assessment Method (SPAM) and Situation Awareness Global Assessment Technique (SAGAT) and performance, identifying a correlation among them. Further research investigated the effect of the amount of information presented in the display on performance, trust and SA (Marusich et al., 2016), reporting a reduction in self-reported SA as a result of an increased amount of task relevant information, meaning increased task-relevant information, despite being accurate, might not help with decision making (Marusich et al., 2016). Researchers also have investigated the effect of the type of information presented on the SA of mobile crane operators; they identified a general trend in improvement in operator performance and SA with the use of a virtually reconstructed visualization of a lift scene (assistance system) over traditional systems (Fang, Cho, Durso, & Seo, 2018). In addition to mobile crane monitoring and operations, studies have been conducted investigating the effect of situation-augmented displays for UAV monitoring (Lu, Horng, & Chao, 2013), the findings suggesting that situation-augmented displays may provide sufficient situation awareness to improve user performance (Lu et al., 2013). The application of an SA framework to investigate various information presentation strategies can be seen in defense research as well. A recent study investigated the effect of

presentation modality, auditory vs. visual and message presentation rate on the SA and the cognitive load of soldiers (Hollands, Spivak, & Kramkowski, 2019). The findings revealed that visual messages and higher message presentation rate resulted in higher cognitive load and reduced SA. Similar studies have been conducted in the healthcare domain as well, for example, a study investigating the effect of head-worn display (HWD) providing continuous patient information on the SA of nursing students while responding to patient alarm. The researchers observed that the participants' responses to SA questions were more accurate when using HWD compared to the alarm only condition (Pascale et al., 2019). Researchers have also investigated the effect of other decision aids such as a checklist on SA. For example, one such study investigated if the use of a checklist improves SA during physician handoffs in a pediatric emergency department. Participants in this study reported an improvement in their SA following the use of a standardized checklist (Mullan, Macias, Hsu, Alam, & Patel, 2015).

However, no research has investigated the effect of decision aids on the SA, performance and workload of infrastructure inspectors. More specifically, to date, no studies have been conducted with windstorm risk engineers. While researchers have investigated the potential of using Augmented Reality (AR)-based systems for flood visualization (Haynes, Hehl-Lange, & Lange, 2018), none has looked at the situation awareness requirements and performance of inspectors. In the study reported here, the researchers investigated how various visualization techniques can be designed to improve the situation awareness of risk engineers. The checklist and predictive display based context-enabled visual decision aids used here were designed based on the findings from a

qualitative study investigating the sensemaking process and SA requirements of risk engineers (Agnisarman et al., 2018). In addition, the principles proposed by Endsley for designing for situation awareness were also incorporated in the decision aids (Endsley, 2016). More specifically, this study designed and tested a checklist-based and predictive display-based decision aids. While risk engineers currently use a high-level checklist, it is not standardized. The checklist used in this study was reviewed by the SME, and the predictive display used in this research is a novel idea which has not yet been used for this application. To investigate the effectiveness of these decision aids, the researchers asked the following questions:

#### *Research questions*

*RQ1:* What is the effect of various context-based visual decision aids on the SA of the participants?

*RQ2:* What is the effect of various context-based visual decision aids on the performance of the participants?

*RQ3:* How does the type of context-based visual decision aid affect the cognitive load imposed on the participants?

#### *Hypotheses*

These research questions led to the following hypotheses:

*H1:* SA will increase when the type of visualization changes from no visual aid to predictive display based visual aid.

*H2:* Performance will increase when the type of visualization changes from no visual aid to predictive display based visual aid.

H3: Cognitive load will decrease when the type of visualization changes from no visual aid to predictive display based visual aid

## METHOD

### *Study sample*

Junior/Senior or graduate level civil engineering or construction science and management students were recruited for the study. This study sample was chosen to simulate the technical skills of actual windstorm risk engineers. Since it focused on a specific sample of civil/construction engineering students, recruiting 90 participants as suggested by power analysis was not feasible. Thus, only 65 participants, ranging from 20 to 41 years old ( $M = 23.35$ ,  $SD = 3.37$ ) were recruited for this study. More demographic information can be found in Table 4.1.

Table 4.1. Demographic characteristics of the participants

Variable (N = 65)	N	%
<b>Gender</b>		
Female	13	20
Male	52	80
<b>Race</b>		
White	39	60
Asian	18	28
Black/African American	5	8
Other	3	4
<b>Major</b>		
Civil Engineering	55	85

Construction	10	15
Science		
<b>Degree Pursuing</b>		
Undergraduate	37	57
Graduate	17	26
Doctorate	11	17

---

### *Apparatus*

This study used a Dell desktop computer with an Intel(R) Xeon(R) CPU E5-1620 v4 processor and a Quadro FX 5800 GPU to run the simulations of a windstorm risk survey. An LG ultralight monitor with a diagonal dimension of 38.8 inches was used as the display. The simulations were developed using Unity game engine (*Unity, 2005*). A laptop computer was used to administer the questionnaires prior to, during and after the study through Qualtrics Research Suite (*Qualtrics, 2005*). The experiment set up can be seen in Figure 4.1. Appendix F shows the consent form used in the study.



Figure 4.1. Experimental setup

### *Simulation*

The participants completed this study in a simulated environment. An academic building located within a 10-miles radius of the Atlantic Coast was used as the simulated scenario. The exposure category used in this study was Category C with generally open terrain with limited obstructions (“Windexpo,” 2019). The location has only two buildings. The front yard of the main academic building had a pond and the backyard had a lake. The building had a number of pieces of rooftop equipment ranging from antennas to duct work. The rooftop also had certain issues including ponding, missing fasteners, a flashing issue, a membrane fissure and clogged drains. Figure 4.2 illustrates four example images of the simulation used in this study.

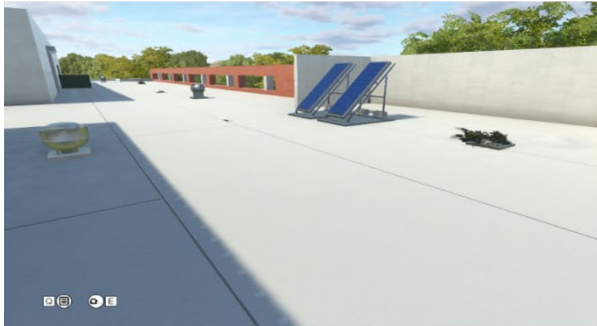




a. Roof parapet and rooftop equipment



b. Aerial view of the building



c. Rooftop equipment



d. Perspective view of the building

Figure 4.2. A few screenshots from the simulation

### *Visualization stimuli development*

Contextual visual aids can be developed following SA design principles (Endsley, 2016) to improve the situation awareness of novice as well as experienced users. The requirements supporting SA in this domain were identified from qualitative research investigating the sensemaking process (Agnisarman et al., 2018). The following design guidelines proposed by Endsley (2016) to design for SA were used as the guidelines while developing visualization techniques: (1) organize information around goals, (2) present Level 2 information directly, (3) provide assistance for Level 3 SA projections, (4) support global SA, (5) support trade-offs between goal driven and data-driven processing, (6) make critical cues for schema activation salient, (7) take advantage of parallel processing

capabilities, and (8) use information processing carefully. The information presented in this study was decided based on the results of the previous research (Agnisarman et al., 2018). The context based visual aids developed here were expected to support the situation awareness requirements of windstorm risk engineers.

#### *Scenarios and tasks completed*

To develop the study scenarios, we considered the various components of a building as defined by Unanwa (1997): the roof covering, the roof sheathing and roof frame, the building envelope, the building occupancy and the structural system. These building components were then used to develop the simulation for this study. The tasks that needed to be completed in the risk assessment of the building were designed based on the findings from the qualitative research (Agnisarman et al., 2018). The participants completed the following tasks validated by the SME:

- Investigating the surroundings to understand missile and flood exposure
- Observing roof underdeck, roof condition, flashing, roof deck, and attachments and obtaining building dimensions
- Investigating rooftop equipment to verify the sufficiency of the securing method
- Investigating building envelop (windows, dock doors, External Insulation Finishing System (EIFS))

#### *Independent variables*

This study included the following independent variables:

*Type of context-based visual aids presented (3 levels):* The context-based visual aids supporting SA functioned as the between-subjects variable in the simulation at three levels:

- No visual aid/control condition -- In this condition, the participants were not provided any visual decision aids. They had to walk through the simulation and perform various inspection activities. They were given a sheet of paper listing the tasks they needed to complete.
- Visualizations aiding users to perceive and gather information in the environment -- This type of visual aid that helps users perceive and gather information in the environment are shown in Figure 4.3. This text-based visual aid used here prompts participants to perceive relevant cues in the environment and comprehend them to make sense of the information. Achieving even Level 1 SA can be challenging, especially for novice engineers.
- Predictive visualization -- This type of visualization includes the elements of checklist-based visualization in addition to an interactive display of the behavior of the components of the building in the event of a hurricane causing severe damage (Damage State 4 as defined in HAZUZ) as illustrated in Figure 4.4. Severe damage involves major window damage or roof sheathing loss, major roof cover loss, and/or extensive damage to the interior from water (*Hazus Hurricane Model User Guidance*, 2018; Liao, 2007). However, this visualization shows only some possibilities of what could happen if there is a severe weather condition. What could actually happen will depend on several uncertain factors such as age of the infrastructure system, wind speed, location and materials. This visualization type is expected to help the participants form a more accurate mental model of the future

state of the building infrastructure. The participants were not able to access both the predictive display and the checklist at the same time.

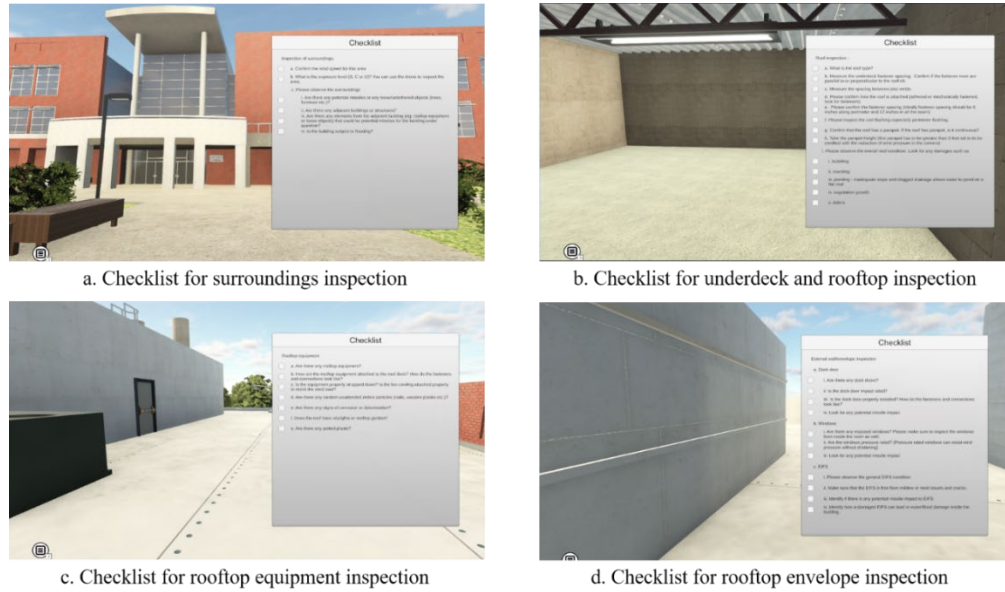


Figure 4.3. Examples of the checklist used in the study

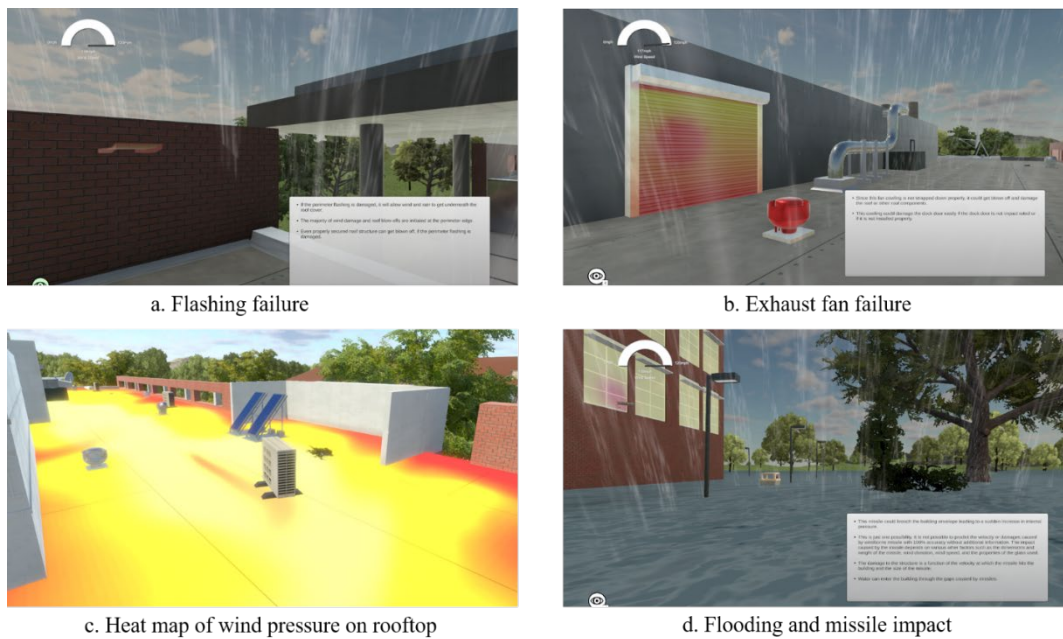


Figure 4.4. Examples of the predictive display used in the study

### *Dependent variables*

*Situation awareness:* An adaptation of the Situation Awareness Global Assessment Technique (SAGAT) was used to assess the SA of the participants. Developed to assess the SA requirements of operators across all of its elements in the aviation domain (Endsley, 1995). SAGAT is a global measure based on the 3-level theory of SA proposed by Endsley (1995), this technique objectively measures the SA requirements of operators at three different levels of SA using a freeze probe protocol. A higher level of accuracy in the operator's answer is attributed to higher levels of SA. The method requires the simulation to freeze at randomly selected times to probe the operators about their perceptions of the situation at that time. The simulation screens are blanked during the freezes.

As no SAGAT queries exist for infrastructure risk inspection domain, the queries used in this research were developed based on the results of qualitative research (Agnisarman et al., 2018). In addition, in this study, these queries were not administered at randomly selected times; rather they were administered at predefined times as was done in a previous study investigating the SA of medical trainees (Gardner, Kosemund, & Martinez, 2017). The questions were presented at five pre-selected intervals during the simulation. Each set was administered following the completion of each task except for the second task (inspection of roof underdeck, roof condition, flashing, roof deck, attachments and obtaining building dimensions). As this task involved more steps than the other tasks, the simulation froze once during the task and after task completion. Appendix G illustrates the SAGAT questionnaires used.

*Workload:* Uncertainty or ambiguity in information leads to increased cognitive load while making sense of such information (Block, 2013; Zuk & Carpendale, 2006). Visualizing these uncertainties will facilitate decision making. However, adding additional elements about uncertainties in the visualization can, in turn, increase the cognitive load on users (Block, 2013). Ideally, the integrated visualization design proposed in this study should result in decreased cognitive load. Though measuring cognitive load directly can be challenging, this study used workload as an indirect measure of it (Block, 2013). The workload was subjectively measured using The National Aeronautics and Space Administration Task Load Index (NASA-TLX) questionnaire, a multidimensional instrument used to measure the workload experienced to evaluate a task, technology or system (Hart, 2006; Hart & Staveland, 1988).

*Performance:* Higher SA does not guarantee improved performance. According to Endsley and Garland (Mica R. Endsley & Garland, 2000), there is only a probabilistic relationship between SA and performance. Higher situation awareness increases the probability of good decisions and good performance (Endsley & Garland, 2000), meaning a direct correlation between SA and performance may be absent. In this research, the performance of participants was measured to study the improvement, if any, as a result of using context-based visual decision aids using a multidimensional approach. A performance questionnaire was designed using the format of a typical school exam, with each correct response contributing to the overall score determined as the net sum of correct and wrong responses. This performance test was designed based on the tasks assigned to the participants, and the survey asked questions about the tasks completed in the simulation.

Though the difference between the SAGAT questionnaire and the performance questionnaire is subtle, the former does not include procedural questions. The performance test was validated by the SME. This questionnaire can be found in Appendix H. Additionally, performance was objectively tracked as the area covered by the participants and the time taken to complete the assigned tasks.

### *Procedure*

To examine the context-based visual decision aids, the entire inspection scenario was simulated using Unity game engine. The complexity of the inspection tasks was simplified significantly for novice participants. This study used a between-subjects experimental design, with one participant being exposed to only one study condition. The study condition was randomly assigned to the participants. The study began with the researcher greeting the participant and briefing each on the study procedure. This step was followed by the participants signing the consent form and then completing a demographic questionnaire. Participants then watched the training video explaining the windstorm risk inspection process and the various steps involved in it. More specifically, the video explained and exemplified the types of issues observed in the real-world as well as the tasks the participants were expected to complete. Next, the participants were randomly assigned to one of the study conditions, followed by the completion of a training scenario in a simulated environment, which used the simulation of a warehouse building with various pieces of rooftop equipment. Through this simulation, participants became familiar

with the navigation controls and decision aids (only for the participants in the decision aid condition).

The participants were then introduced to the study condition and the tasks they were assigned to complete in the simulation. They were able to take notes during the inspection process using the pen and paper provided. After each task, the participants were asked to complete the SAGAT questions; however, they were not allowed to consult their notes while completing the questionnaire. Upon completion of all four tasks, they completed the performance and NASA-TLX questionnaires; while completing the performance questionnaire, participants were able to use their notes. They then participated in a retrospective think aloud session where they were asked to reflect on their performance. This procedure is illustrated in Figure 4.5.



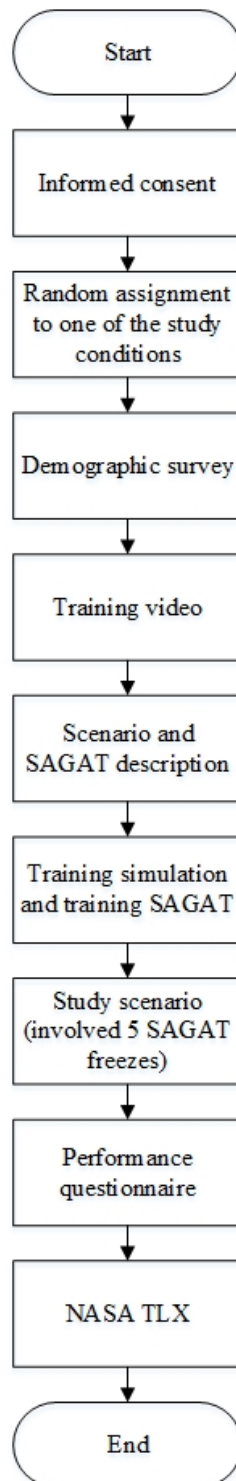


Figure 4.5. Flow chart outlining experiment procedure

### *Data analysis*

R language for statistical computing (R Core Team, 2019) was used for data analysis. Outliers were identified and eliminated using standardized deviance residuals, standardized residuals and Cook's Distance. The SAGAT responses were analyzed using multilevel binary logistic regression with a logit link function. For this variable, an additional independent variable indicating the SA level was also considered in the analysis. The SAGAT questions were categorized into three levels based on the SA level each represented. Questions related to the first level of SA (the perception phase) were categorized under Level 1 SA, questions related to the second level of SA (the comprehension phase) were categorized under Level 2 SA and questions related to the third level of SA (the prediction phase) were categorized under Level 3 SA. This variable was included in the analysis to identify the specific effects of the decision aids on the different levels of SA of the participants. Following are the equations for the multilevel binary logistic regression (Tabachnick, Fidell, & Ullman, 2007). Random slopes were not considered in the analysis.

$$\ln \left[ \frac{p_{ij}}{1 - p_{ij}} \right] = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij} \quad (4.1)$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j} \quad (4.2)$$

In this equation:

- $p_{ij}$ =the conditional probability that the event  $Y_{ij}$  occurs or  $p(Y_{ij}=1)$ .
- $\beta_{0j}$ =intercept that varies
- $\beta_{1j}$ =slope
- $X_{ij}$ =level 1 predictor

- $e_{ij}$ =the deviation of an individual from his or her group mean
- $\gamma_{00}$ =average intercept when all the predictors are zero (fixed effect)
- $\gamma_{01}$ =slope for the relationship between the DV  $Y_{ij}$  and level 2 IV  $Z$
- $u_{0j}$ =deviation from average intercept for group  $j$  (random effect)
- $W_j$ =level 2 predictor

Outliers were identified using Cook's Distance and standardized deviance. Plots were also investigated to identify influential cases.

Workload data collected using the NASA-TLX and the performance data were analyzed using one-way between-subjects ANOVA. These dependent variables were tested for normality using the Shapiro-Wilk test, and extreme outliers were assessed by an examination of the standardized residuals for values greater than  $\pm 3$ ; there was homogeneity of variances, as assessed by Levene's test of homogeneity of variances. In addition, Cook's Distance was used to identify any influential cases.

## RESULTS

### *SAGAT*

SAGAT responses were coded as 1 (if the response is correct) and 0 (if the response is wrong). Each SAGAT query was analyzed individually to allow for comparisons to be made among the different conditions (Stanton, Hedge, Brookhuis, Salas, & Hendrick, 2004). Separate multilevel logistic regression analyses were conducted to analyze the five sets of SAGAT responses recorded following the simulation freeze. The lme4 package available in R was used for analyzing SAGT responses (Bates, Mächler, Bolker, & Walker, 2015). The multilevel logistic regression model for the SAGAT queries was built

iteratively, with the intercept only model being used as the baseline and the final model including the types of context based visual aids presented and the SA levels and/or the interaction between the types of visual aids and the SA level. No extreme data points were identified as assessed by deviance residuals and Cook's Distance.

*Inspection of surroundings (SAGAT 1):* The first set of SAGAT responses was recorded following the completion of the first task, which involved the inspection of building surroundings to identify the exposure level and to evaluate missile impact to the building. Following this task, the first SAGAT questionnaire containing 10 questions was administered. The multilevel model was built iteratively. Table 2 illustrates the details of the iterative model building.

A test of the full model with 2 independent variable and one 2-way interaction effect against an intercept only model was significant,  $\chi^2(9, N=65) = 111.87, p < 0.001, R^2_L = 0.13$ , indicating that the predictors as a whole reliably distinguished participants who correctly answered the SAGAT questionnaire and those who did not. The main effects of type of visual decision aid ( $\Delta\chi^2 = 37.53, p < 0.001$ ) and SA level are significant ( $\Delta\chi^2 = 36.66, p < 0.001$ ). The interaction between these 2 factor variables is significant with  $\Delta\chi^2 = 17.42, p = 0.002$ . Further analysis was conducted to investigate the nature of this interaction. Table 3 shows the mean values of the variables, and Figure 4.6 illustrates this interaction effect.

As illustrated in Figure 4.6, participants exposed to the checklist and predictive display condition had higher SA compared to participants exposed to the control condition. However, this difference is moderated by the SA level. More specifically, there was no

significant difference in the SA among participants exposed to the control, checklist and predictive conditions when they were questioned on their Level 1 SA. Participants in the checklist condition ( $b = 1.625$ ,  $p = 0.02$ ,  $OR = 5.08$ , (95% CI: 1.10, 23.36)) and predictive display condition ( $b = 2.98$ ,  $p = 0.0001$ ,  $OR = 19.59$ , (95% CI [2.71, 141.35])) had significantly higher SA than participants in the control condition when they were questioned on their Level 2 SA. There was no significant difference between the SA of participants exposed to the checklist condition and the predictive display condition when questioned on their Level 2 SA ( $b = 1.35$ ,  $p = 0.47$ ,  $OR = 3.86$ , (95% CI: 0.53, 28.11)). Similarly, participants in the checklist condition ( $b = 3.43$ ,  $p = 0.03$ ,  $OR = 30.97$ , (95% CI: 1.12, 850.39)) and the predictive display condition ( $b = 2.71$ ,  $p = 0.02$ ,  $OR = 15.11$ , (95% CI [1.25, 182.24])) had significantly higher SA than participants in the control condition when they were probed on their Level 3 SA. However, there is no significant difference between the SA of participants exposed to the predictive display condition and the checklist condition when probed on their Level 3 SA ( $b = -0.49$ ,  $p = 0.57$ ,  $OR = 0.49$ , (95% CI [0.01, 23.46])).

Table 4.2. Model summary for multilevel logistic regression analysis for inspection of surroundings (SAGAT 1)

Variable	Model1				Model2 ( $\Delta\chi^2 = 139.00$ , $df = 1$ , $p < 0.001$ ), $R^2_L = 0.14$				Model3 ( $\Delta\chi^2 = 37.70$ , $df = 2$ , $p < 0.001$ ), $\Delta R^2_L = 0.05$ , $R^2_L = 0.08$				Model4 ( $\Delta\chi^2 = 82.96$ , $df = 2$ , $p < 0.001$ ), $\Delta R^2_L = 0.02$ , $R^2_L = 0.10$				Model5 ( $\Delta\chi^2 = 9.78$ , $df = 4$ , $p = 0.04$ ), $\Delta R^2_L = 0.03$ , $R^2_L = 0.13$			
	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper
Constant	1.25 (0.09)	3.49	2.90	4.20	1.42 (0.15)	4.14	3.13	5.79	0.41 (0.16)	1.51	1.10	2.11	0.48 (0.18)	1.62	1.13	2.37	0.79 (0.21)	2.21	1.46	3.44
Experimental Condition (type of visualization)																				
Checklist									1.25 (0.25)	3.49	2.14	5.94	1.29 (0.26)	3.63	2.19	6.29	0.81 (0.33)	2.26	1.20	4.39
Predictive Display SA level									1.68 (0.28)	5.36	3.16	9.61	1.73 (0.29)	5.62	3.27	10.27	1.05 (0.34)	2.85	1.48	5.73
Level 2													-0.70 (0.24)	0.49	0.31	0.79	-1.40 (0.38)	0.25	0.11	0.51
Level 3													0.42 (0.29)	1.53	0.88	2.74	-0.39 (0.37)	0.68	0.32	1.42
Interaction between Condition and SA Level																				
Checklist: SAlevel2																	0.81 (0.56)	2.25	0.76	6.94
Predictive display: SAlevel2																	1.93 (0.70)	6.88	1.87	30.20
Checklist: SAlevel3																	2.62 (1.10)	13.73	2.26	267.11
Predictive display: SAlevel3																	1.67 (0.85)	5.31	1.17	38.49

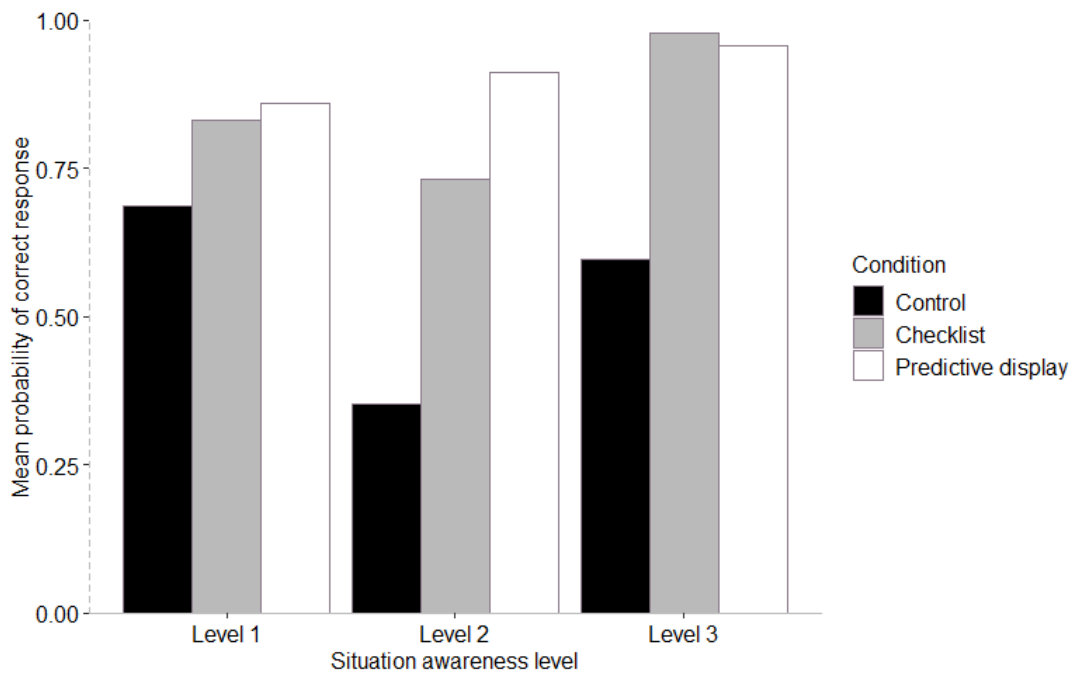


Figure 4.6. Interaction effect of type of SA level on the relationship between SA and types of visualization presented (inspection of surroundings — SAGAT 1)

Table 4.3. Mean probability of correctly answering SAGAT questions for inspection of surroundings task (SAGAT 1)

		SA level		
		Level 1	Level 2	Level 3
Type of visualization	Control	0.69	0.35	0.60
	Checklist	0.83	0.73	0.98
	Predictive display	0.86	0.91	0.96

*Inspection of underdeck and rooftop (SAGAT 2):* The second set of SAGAT responses was recorded during the second task, which involved underdeck inspection and rooftop inspection. More specifically, the participants measured the underdeck and rooftop fastener spacing and the distance between joist welded connections and inspected the general condition of the roof deck. In the middle of this task, the second SAGAT questionnaire containing 8 questions was administered, and the multilevel model was again built iteratively. Table 4 illustrates the details of iterative model building.

Table 4.4. Model summary for multilevel logistic regression analysis for inspection of underdeck and rooftop (SAGAT 2)

Variable	Model1				Model2 ( $\Delta\chi^2 = 139.00$ , $df = 1$ , $p < 0.001$ ), $R^2_L = 0.06$				Model3 ( $\Delta\chi^2 = 37.70$ , $df = 2$ , $p < 0.001$ ), $\Delta R^2_L = 0.06$ , $R^2_L = 0.11$				Model4 ( $\Delta\chi^2 = 82.96$ , $df = 2$ , $p < 0.001$ ), $\Delta R^2_L = 0.14$ , $R^2_L = 0.23$				Model5 ( $\Delta\chi^2 = 9.78$ , $df = 4$ , $p = 0.04$ ), $\Delta R^2_L = 0.02$ , $R^2_L = 0.25$			
	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper
Constant	0.63 (0.09)	1.87	1.57	2.25	0.79 (0.17)	2.19	1.58	3.16	-0.31 (0.20)	0.74	0.48	1.10	1.05 (0.31)	2.86	1.58	5.43	1.33 (0.37)	3.80	1.89	8.24
Experimental Condition (type of visualization)																				
Checklist									1.06 (0.30)	2.88	1.62	5.36	1.35 (0.38)	3.86	1.86	8.47	0.88 (0.58)	2.41	0.79	7.86
Predictive Display									2.10 (0.32)	8.17	4.43	16.26	2.59 (0.41)	13.31	6.21	31.65	1.79 (0.68)	5.97	1.67	25.51
Situation awareness level																				
Level 2													-2.23 (0.29)	0.11	0.06	0.19	-2.67 (0.44)	0.07	0.03	0.16
Level 3													-2.36 (0.39)	0.09	0.04	0.20	-2.98 (0.68)	0.05	0.01	0.18
Interaction between Condition and SA Level																				
Checklist: SAlevel2																	2.52 (1.15)	12.45	1.42	143.51
Predictive display: SAlevel2																	0.85 (0.63)	2.35	0.67	8.06
Checklist: SAlevel3																	0.83 (0.73)	2.28	0.50	9.09
Predictive display: SAlevel3																	0.19 (0.92)	1.21	0.20	7.78



A test of the full model with 2 independent variables and one 2-way interaction effect against an intercept only model was significant,  $\chi^2(9, N=65) = 237.02, p < 0.001$ ,  $R^2L = 0.25$ , indicating that the predictors as a whole reliably distinguished participants who correctly answered the SAGAT questionnaire and those who did not. The main effects of type of visual decision aid ( $\Delta\chi^2 = 17.42, p = 0.002$ ) and SA level are significant ( $\Delta\chi^2 = 82.96, p < 0.001$ ). The interaction between these 2 factor variables is significant with  $\Delta\chi^2 = 9.78, p = 0.04$ . Further analysis was conducted to examine the nature of this interaction. Table 3 shows the mean values of the variables, and Figure 4.7 illustrates this interaction effect.

As illustrated in Figure 4.7, participants exposed to the checklist and the predictive display condition had higher situation awareness compared to participants exposed to the control condition. However, this difference is moderated by the SA level. More specifically, there was no significant difference in the SA among participants exposed to the control, checklist and predictive conditions when they were probed on their Level 1 SA. However, participants in the checklist condition ( $b = 1.73, p = 0.005, OR = 5.66, (95\% CI, 1.36 \text{ to } 23.62)$ ) and predictive display condition ( $b = 2.61, p < 0.001, OR = 13.62, (95\% CI [3.11, 59.68])$ ) had significantly higher SA than participants in the control condition when they were probed on their Level 2 SA. There was no significant difference between the SA of participants exposed to the checklist condition and the predictive display condition when probed on their Level 2 SA ( $b = 0.88, p = 0.56, OR = 2.41, (95\% CI, 0.61 \text{ to } 9.57)$ ). Similarly, participants in the predictive display condition had significantly higher SA than participants in the control condition ( $b = 4.31, p < 0.001, OR = 74.31, (95\% CI$

[3.17, 1740.11])) and participants in the checklist condition ( $b = 3.24, p = 0.002, OR = 25.41, (95\% CI: 1.30, 496.28)$ ) when they were probed on their Level 3 SA. However, there was no significant difference between the SA of participants exposed to the checklist condition and the control condition ( $b = 1.07, p = 0.92, OR = 2.92, (95\% CI [0.24, 36.07])$ ) when probed on their Level 3 SA.

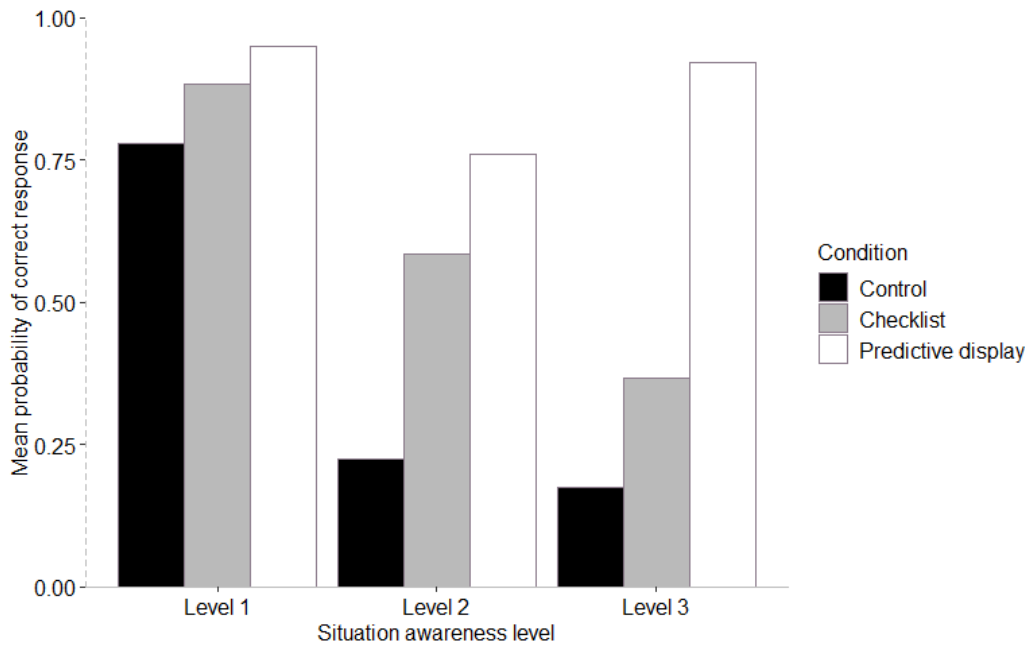


Figure 4.7. Interaction effect of type of SA level on the relationship between SA and types of visualization presented (inspection of underdeck and rooftop — SAGAT 2)

Table 4.5. Mean probability of correctly answering SAGAT questions for underdeck and rooftop inspection task (SAGAT 2)

		SA level		
		Level 1	Level 2	Level 3
Type of visualization	Control	0.78	0.22	0.18
	Checklist	0.88	0.59	0.37
	Predictive display	0.95	0.76	0.92

*Inspection of underdeck and rooftop continuation (SAGAT 3):* The third set of SAGAT responses was recorded following the completion of the second task. This questionnaire

contained 8 questions, and the multilevel model was built iteratively. Table 6 illustrates the details of this iterative model building. As this table shows, the model containing the main effect of SA level and the model containing the main effect of SA level and types of visualization and the interaction effect of these two variables are not significantly different from the model containing only the main effect of type of visualization. Thus, the main effect of SA level and the interaction effect between the type of visualization and SA level were removed from the model. Model 3 is used as the final model.

A test of the model with type of visualization against the baseline model is significant  $\chi^2(3, N=65) = 127.62, p < 0.001, R^2_L = 0.09$ , indicating that the predictor reliably distinguished participants who correctly answered the SAGAT questionnaire and those who did not. As illustrated in Figure 4.8, participants exposed to the checklist ( $b = 1.24, p = 0.0001, OR = 3.45, (95\% CI [1.70, 6.98])$ ) and the predictive display ( $b = 1.85, p < 0.001, OR = 6.33, (95\% CI [2.95, 13.59])$ ) conditions had higher SA than participants in the control condition. However, there was no significant difference between the SA of participants assigned to the predictive display condition and the checklist condition ( $b = 0.61, p = 0.16, OR = 1.83, (95\% CI [0.84, 4.02])$ ). The mean probability values can be found in Table 4.7.

Table 4.6. Model summary for multilevel logistic regression analysis for the second part of inspection of underdeck and rooftop (SAGAT 3)

Variable	Model1				Model2 ( $\Delta\chi^2 = 143.61$ , $df = 1$ , $p < 0.001$ ), $R^2_L = 0.05$				Model3 ( $\Delta\chi^2 = 30.22$ , $df = 2$ , $p < 0.001$ ), $\Delta R^2_L = 0.04$ , $R^2_L = 0.09$				Model4 ( $\Delta\chi^2 = 3.11$ , $df = 2$ , $p = 0.211$ ), $\Delta R^2_L = 0.004$ , $R^2_L = 0.10$				Model5 ( $\Delta\chi^2 = 2.81$ , $df = 4$ , $p = 0.59$ ), $\Delta R^2_L < 0.001$ , $R^2_L = 0.10$			
	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper
Constant	1.06 (0.09)	2.89	2.43	3.46	1.30 (0.17)	3.68	2.66	5.37	0.23 (0.20)	1.26	0.85	1.92	0.40 (0.24)	1.49	0.94	2.37	0.32 (0.27)	1.38	0.81	2.35
Experimental Condition (type of visualization)																				
Checklist									1.24 (0.30)	3.45	1.92	6.46	1.25 (0.30)	3.48	1.92	11.60	1.58 (0.44)	4.83	2.06	11.33
Predictive Display Situation awareness level									1.85 (0.33)	6.33	3.40	12.63	1.86 (0.33)	6.41	3.37	12.18	1.79 (0.45)	5.97	2.46	14.48
Level 2													-0.41 (0.23)	0.66	0.42	1.05	-0.42 (0.35)	0.66	0.33	1.31
Level 3													-0.13 (0.24)	0.88	0.55	1.40	0.14 (0.35)	1.15	0.58	2.30
Interaction between Condition and SA Level																				
Checklist: SA Level 2																	-0.32 (0.54)	0.73	0.25	2.13
Predictive display: SA Level 2																	0.45 (0.61)	1.58	0.48	5.24
Checklist: SA Level 3																	-0.71 (0.55)	0.49	0.17	1.47
Predictive display: SA Level 3																	-0.25 (0.60)	0.78	0.24	2.55

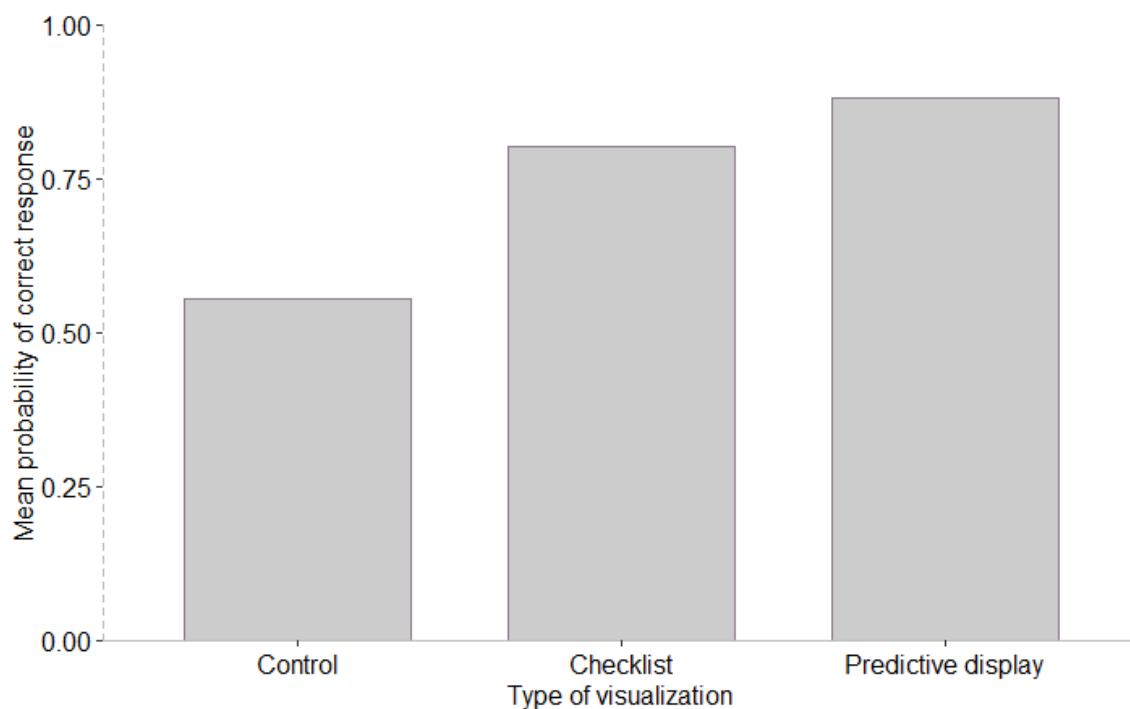


Figure 4.8. Main effect of the type of visualization presented (inspection of underdeck and rooftop continuation — SAGAT 3)

Table 4.7. Mean probability of correctly answering SAGAT questions for the second part of underdeck and rooftop inspection task (SAGAT 3)

Type of visualization	
Control	0.55
Checklist	0.80
Predictive display	0.88

*Inspection of rooftop equipment (SAGAT 4):* The fourth set of SAGAT responses was recorded following the completion of the third task, which involved the inspection of rooftop equipment. Participants had to inspect how the equipment on rooftop is fastened to the roof in addition to how equipment and other components on the roof will be affected in the event of extreme weather conditions. The SAGAT questionnaire contained 8 questions, and the multilevel model was built iteratively. Table 4.8 illustrates the details of the iterative model building. As shown in this table, the model containing the interaction

effect of the type of visualization and the SA level is not significantly different from the model containing only the main effects of these variables. Thus, the interaction effect between the type of visualization and the SA level was removed from the model. Model 4 is used as the final model.

A test of the model with the main effect of type of visualization and SA level against the baseline model is significant  $\chi^2(5, N=65) = 135.06, p < 0.001, R^2_L = 0.15$ , indicating that the predictors reliably distinguished participants who correctly answered the SAGAT questionnaire and those who did not. The main effects of type of visual decision aid ( $\Delta\chi^2 = 37.75, p < 0.001$ ) and SA level are significant ( $\Delta\chi^2 = 33.53, p < 0.001$ ). As illustrated in Figure 4.9, participants assigned to the predictive display conditions had higher SA than participants in the checklist condition ( $b = 1.45, p = 0.001, OR = 4.26, (95\% CI [1.43, 12.75])$ ) and the control condition ( $b = 2.23, p < 0.001, OR = 9.26, (95\% CI [3.04, 28.21])$ ). However, there was no significant difference between the SA of participants exposed to the control condition and the checklist condition ( $b = 0.78, p = 0.18, OR = 2.17, (95\% CI [0.86, 5.47])$ ). The mean probability value can be found in Table 4.9.

As illustrated in Figure 4.10, the participants' Level 2 SA was significantly lower than their Level 1 SA ( $b = -1.56, p < 0.001, OR = 0.21, (95\% CI [0.09, 0.50])$ ) and Level 3 SA ( $b = -1.04, p = 0.003, OR = 0.353, (95\% CI [0.15, 0.81])$ ). However, no significant difference was observed between Level 1 and Level 3 SA ( $b = 0.53, p = 0.51, OR = 1.70, (95\% CI [0.76, 3.79])$ ). The mean probability value can be found in Table 4.9.

Table 4.8. Model summary for multilevel logistic regression analysis for inspection of rooftop equipment (SAGAT 4)

Variable	Model1				Model2 ( $\Delta\chi^2 = 109.76$ , $df = 1$ , $p < 0.001$ ), $R^2_L = 0.04$				Model3 ( $\Delta\chi^2 = 37.73$ $df = 2$ , $p < 0.001$ ), $\Delta R^2_L = 0.06$ , $R^2_L = 0.09$				Model4 ( $\Delta\chi^2 = 33.53$ , $df = 2$ , $p < 0.001$ ), $\Delta R^2_L = 0.06$ , $R^2_L = 0.15$				Model5 ( $\Delta\chi^2 = 4.91$ , $df = 4$ , $p = 0.30$ ), $\Delta R^2_L < 0.001$ , $R^2_L = 0.16$			
	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper
Constant	0.85 (0.09)	2.33	1.94	2.82	1.00 (0.16)	2.74	2.02	3.90	0.10 (0.19)	1.10	0.76	1.61	0.69 (0.25)	1.99	1.21	3.35	0.66 (0.30)	1.93	1.08	3.58
Experimental Condition (type of visualization)																				
Checklist									0.70 (0.27)	2.02	1.19	3.54	0.78 (0.30)	2.17	1.21	4.05	0.85 (0.46)	2.33	0.97	5.91
Predictive Display									2.04 (0.33)	7.69	4.16	15.47	2.22 (0.36)	9.26	4.73	20.04	2.24 (0.62)	9.38	3.04	36.85
Situation awareness level																				
Level 2													-1.56 (0.28)	0.21	0.12	0.36	-1.40 (0.44)	0.25	0.10	0.57
Level 3													-0.53 (0.26)	0.59	0.35	0.98	-0.56 (0.38)	0.57	0.27	1.19
Interaction between Condition and SA Level																				
Checklist:																				
SA Level2																	-0.01 (0.62)	0.99	0.29	3.37
Predictive display:																	-0.56 (0.76)	0.57	0.12	2.43
SA Level2																				
Checklist:																				
SA Level3																	-0.20 (0.56)	0.82	0.27	2.47
Predictive display:																	0.87 (0.87)	2.39	0.43	14.68
SA Level3																				

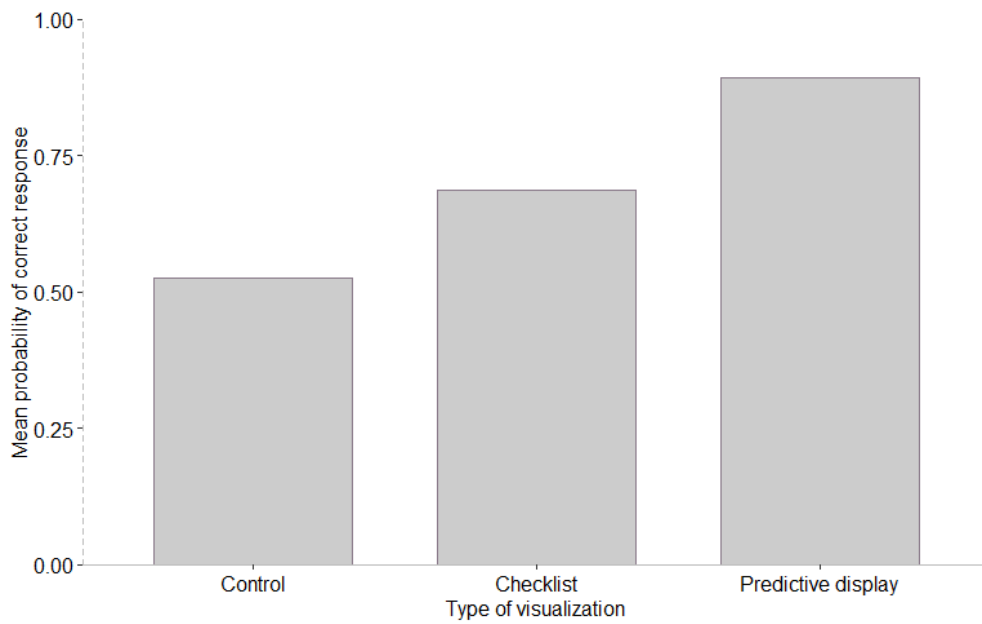


Figure 4.9. Main effect of the type of visualization presented (inspection of rooftop equipment — SAGAT 4)

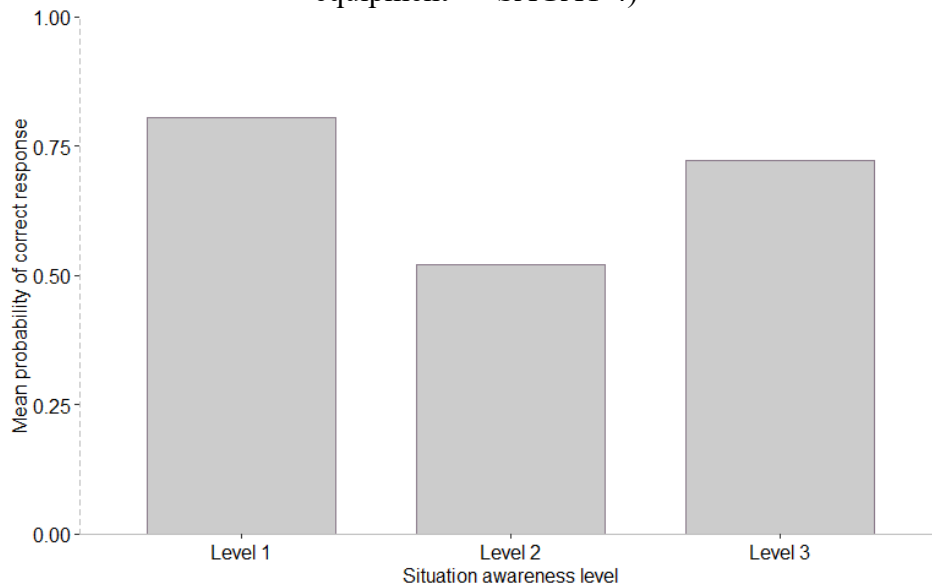


Figure 4.10. Main effect of situation awareness level (inspection of rooftop equipment — SAGAT 4)



Table 4.9. Mean probability of correctly answering SAGAT questions for inspection of rooftop equipment (SAGAT 4)

Types of visualization		SA level	
Control	0.52	Level 1	0.81
Checklist	0.69	Level 2	0.52
Predictive display	0.89	Level 3	0.72

*Inspection of envelope (SAGAT 5):* The fifth set of SAGAT responses was recorded following the completion of the fourth and final task, which involved the inspection of the envelope. The envelope included windows, doors/dock doors, and exterior insulation and finish system (EIFS). To make the inspection task less complex, the participants were asked to inspect only the envelope of the rooms on the rooftop. The SAGAT questionnaire contained 8 questions, and the multilevel model was built iteratively. Table 4.10 illustrates the details of the iterative model building. As shown in the table, the model containing the interaction effect of the type of visualization and SA level is not significantly different from the model containing only the main effects of these variables. Thus, the interaction effect between the type of visualization and SA level was removed from the model. Model 4 is used as the final model.

Table 4.10. Model summary for multilevel logistic regression analysis for inspection of envelope (SAGAT 5)

Variable	Model1				Model2 ( $\Delta\chi^2 = 141.82$ , $df = 1$ , $p < 0.001$ ), $R^2_L = 0.06$				Model3 ( $\Delta\chi^2 = 28.08$ , $df = 2$ , $p < 0.001$ ), $\Delta R^2_L = 0.05$ , $R^2_L = 0.10$				Model4 ( $\Delta\chi^2 = 85.93$ , $df = 2$ , $p < 0.001$ ), $\Delta R^2_L = 0.15$ , $R^2_L = 0.23$				Model5 ( $\Delta\chi^2 = 2.12$ , $df = 4$ , $p = 0.71$ ), $\Delta R^2_L = 0.004$ , $R^2_L = 0.24$			
	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper	B (SE)	OR	CI Lower	CI Upper
Constant	0.75 (0.09)	2.11	1.76	2.55	0.94 (0.18)	2.55	1.82	3.72	-0.08 (0.23)	0.92	0.58	1.45	0.89 (0.34)	2.45	1.26	4.92	0.94 (0.38)	2.56	1.22	5.61
Experimental Condition (type of visualization)																				
Checklist									1.02 (0.34)	2.78	1.44	5.35	1.31 (0.43)	3.71	1.60	9.04	1.42 (0.61)	4.12	1.29	14.33
Predictive Display									2.00 (0.37)	7.42	3.40	15.32	2.55 (0.48)	12.79	5.22	35.37	2.11 (0.69)	8.21	2.28	35.58
Situation awareness level																				
Level 2													-2.39 (0.31)	0.09	0.05	0.16	-2.36 (0.46)	0.09	0.04	0.23
Level 3													-0.51 (0.33)	0.60	0.32	1.14	-0.70 (0.46)	0.49	0.20	1.21
Interaction between Condition and SA Level																				
Predictive display: SA Level 2																	-0.23 (0.67)	0.79	0.21	2.93
Predictive display: SA Level 2																	0.35 (0.74)	1.42	0.31	5.91
Checklist: SA Level 3																	-0.01 (0.73)	0.99	0.24	4.16
Predictive display: SA Level 3																	1.31 (1.02)	3.70	0.55	33.84

A test of the model with the main effect of type of visualization and SA level against the baseline model is significant  $\chi^2(5, N=65) = 240.04, p < 0.001, R^2_L = 0.23$ , indicating that the predictors reliably distinguished participants who correctly answered the SAGAT questionnaire and those who did not. The main effect of type of visual decision aid ( $\Delta\chi^2 = 28.33, p < 0.001$ ) and SA level is significant ( $\Delta\chi^2 = 85.93, p < 0.001$ ). As illustrated in Figure 4.11, participants in the predictive display condition had significantly higher SA than participants in the control condition ( $b = 2.55, p < 0.001, OR = 12.80, (95\% CI [2.90, 56.38])$ ). Participants exposed to the checklist conditions had marginally significantly higher SA than participants in the control condition ( $b = 1.31, p = 0.06, OR = 3.71, (95\% CI [0.98, 14.06])$ ). However, there was no significant difference between the SA of participants exposed to the predictive display condition and the checklist condition ( $b = 1.24, p = 0.15, OR = 3.45, (95\% CI [0.82, 14.49])$ ). The mean probability value can be found in Table 4.11.

As illustrated in Figure 4.12, the participants' Level 2 SA was significantly lower than their Level 1 SA ( $b = -2.39, p < 0.001, OR = 0.09, (95\% CI [0.035, 0.24])$ ) and Level 3 SA ( $b = -1.88, p < 0.001, OR = 0.152, (95\% CI [0.057, 0.41])$ ). However, no significant difference was observed between Level 1 and Level 3 SA ( $b = 0.51, p = 0.82, OR = 1.66, (95\% CI [0.61, 4.56])$ ). The mean probability value can be found in Table 4.11. As illustrated in Figure 4.12, the participants' Level 2 SA was significantly lower than their Level 1 SA ( $b = -2.39, p < 0.001, OR = 0.09, (95\% CI [0.035, 0.24])$ ) and Level 3 SA ( $b = -1.88, p < 0.001, OR = 0.152, (95\% CI [0.057, 0.41])$ ). However, no significant difference

was observed between Level 1 and Level 3 SA ( $b = 0.51$ ,  $p = 0.82$ ,  $OR = 1.66$ , (95% CI [0.61, 4.56])). The mean probability value can be found in Table 4.11.

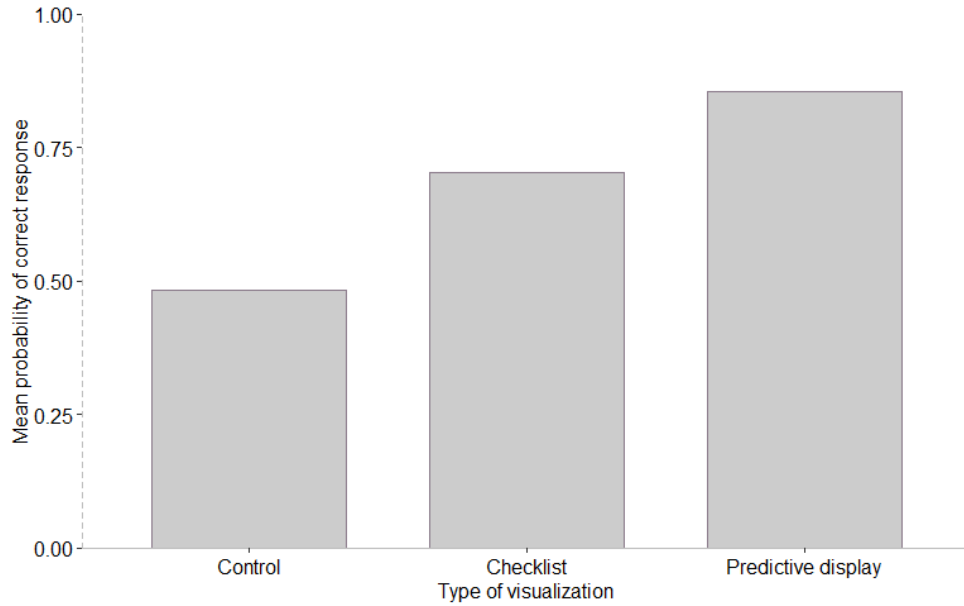


Figure 4.11. Main effect of the type of visualization presented (inspection of envelope — SAGAT 5)

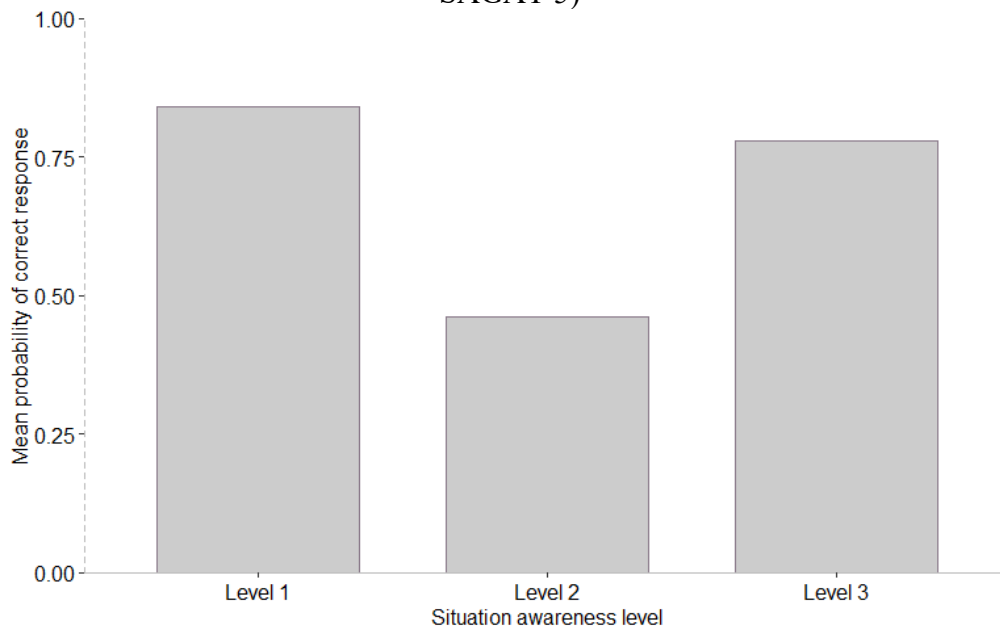


Figure 4.12. Main effect of situation awareness level (inspection of envelope — SAGAT 5)

Table 4.11. Mean probability of correctly answering SAGAT questions for inspection of envelope (SAGAT 5)

Types of visualization		SA level	
Control	0.48	Level 1	0.84
Checklist	0.70	Level 2	0.46
Predictive display	0.86	Level 3	0.78

### *Performance*

The participants' responses to the performance questionnaire was graded and the cumulative score calculated. The maximum possible score was 56, and the individual scores were converted to percentages. The performance score for one participant was missing completely at random (MCAR). Thus, this data point was imputed using the MICE package available in R (Buuren & Groothuis-Oudshoorn, 2011). There was only one standardized residual (3.09) value not within +/-3. No data points were removed for further analysis. In addition, no influential cases were identified using the Cook's Distance method.

A between-subjects ANOVA was conducted to investigate the effect of type of visualization on the performance of the participants. A significant difference in performance was observed among participants exposed to different conditions ( $F(2, 62) = 17.47, p < 0.001, \omega^2 = 0.34$ ). The performance score increased from the control condition ( $M = 54.38, SD = 12.35$ ) to the checklist condition ( $M = 65.83, SD = 14.80$ ) to the predictive display condition ( $M = 76.70, SD = 9.38$ ). A post-hoc analysis with Bonferroni correction revealed that the mean increase in performance from the control condition to the checklist condition (11.45, 95% CI [2.16, 20.7]) was statistically significant ( $p = 0.011$ ).

Additionally, a statistically significant difference in performance was observed between the control condition and the predictive display condition (22.32, 95% CI [13.03, 31.6],  $p < 0.001$ ), and the checklist condition and the predictive display condition (10.87, 95% CI [1.69, 20.1],  $p = 0.015$ ). This effect of type of visualization is illustrated in Figure 4.13.

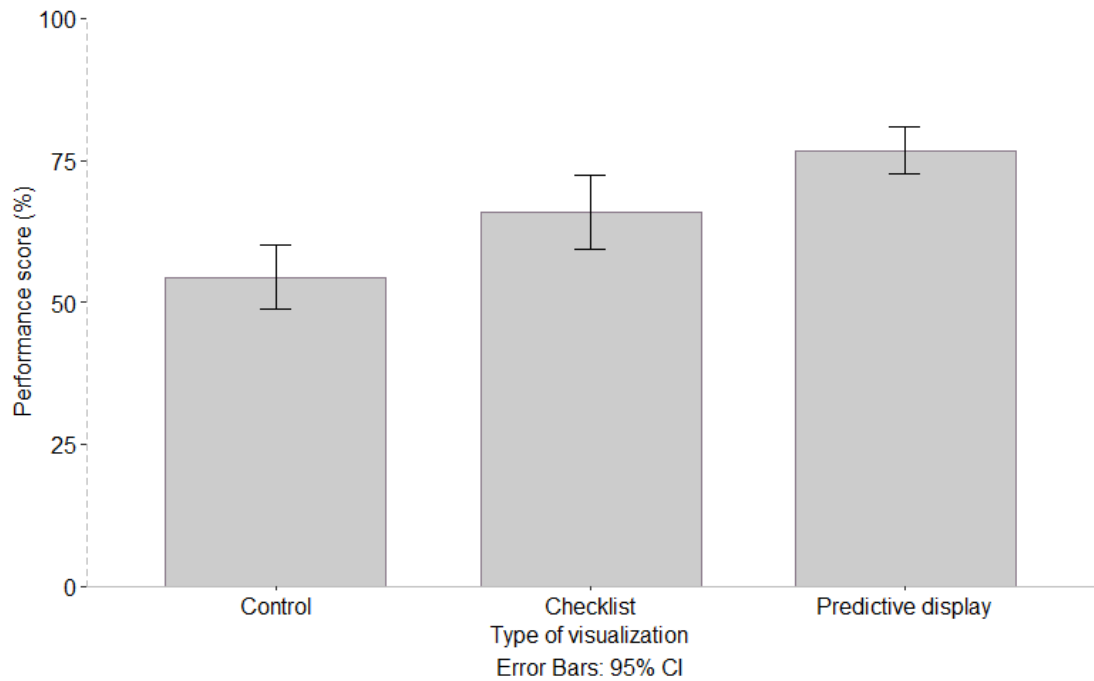


Figure 4.13. Effect of the type of visualization presented on performance

### *Time*

The simulation tracked the time taken to complete the inspection task. One missing data point was imputed using the MICE package. The time data were normally distributed for the control, checklist and predictive display groups. A between-subjects ANOVA was conducted to investigate the effect of type of visualization on the time taken to complete the assigned tasks. A significant difference in time taken was observed among participants

exposed to the different conditions ( $F(2, 62) = 34.40, p < 0.001, \omega^2 = 0.51$ ). As illustrated in Figure 4.14, time taken in seconds to complete the inspection tasks increased from the control condition ( $M = 961.64, SD = 47.03$ ) to the checklist condition ( $M = 1623.24, SD = 64.22$ ) and the predictive display condition ( $M = 1713.61, SD = 88.26$ ). A post-hoc analysis with Bonferroni correction revealed that the mean increase in time taken from the control to the checklist condition ( $661.60, 95\% \text{ CI } [419, 904], p < 0.001$ ) and predictive display condition ( $752.00, 95\% \text{ CI } [509, 995], p < 0.001$ ) is statistically significant. However, no statistically significant difference was observed between the time taken to complete the inspection tasks in the checklist condition and the predictive display condition ( $90.4, 95\% \text{ CI } [-149, 330], p = 0.99$ ).

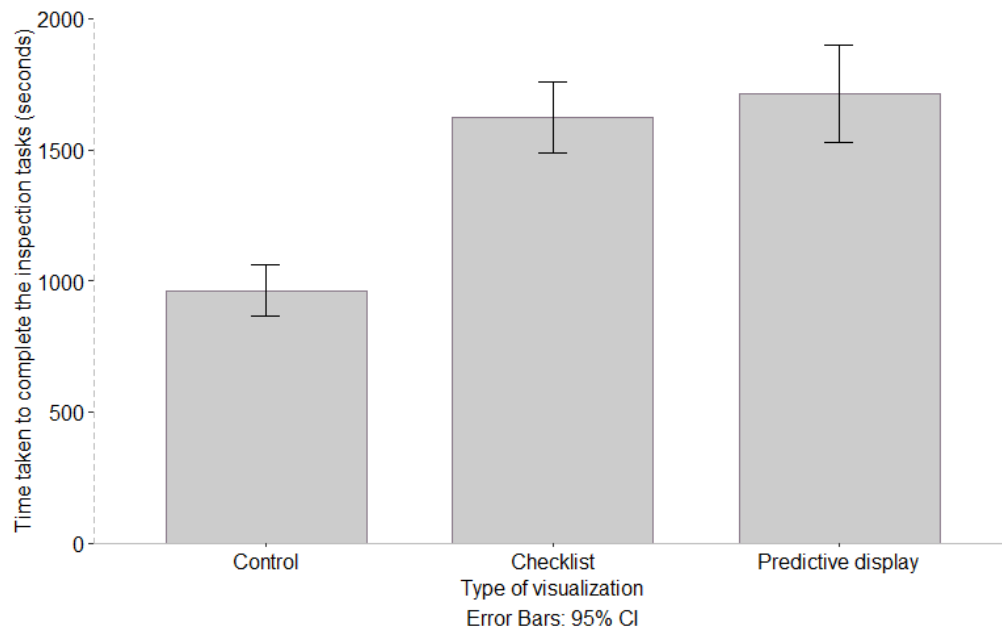


Figure 4.14. Effect of the type of visualization presented on time taken to complete inspection tasks

### *Workload*

*Total workload:* The total workload experienced by the participants while completing the inspection tasks was measured subjectively using the NASA TLX tool. Total workload was normally distributed for the control, checklist and predictive display groups. A between-subjects ANOVA was conducted to investigate the effect of type of visualization on the subjective total workload experienced by the participants. As illustrated in Figure 4.15, total workload decreased from the control condition (M = 52.51, SD = 16.81) to the checklist condition (M = 49.56, SD = 17.46) to the predictive display condition (M = 45.92, SD = 13.74). However, no significant difference in the total workload experienced was observed among participants exposed to the different conditions ( $F(2, 62) = 0.906$ ,  $p = 0.41$ ,  $\omega^2 = -0.003$ ).

*Mental demand:* The perceived mental demand experienced by the participants while completing the inspection tasks was measured subjectively using the NASA TLX tool. Mental demand data was normally distributed for the checklist and predictive display groups. A between-subjects ANOVA was conducted to investigate the effect of type of visualization on the subjective mental demand experienced by the participants. As illustrated in Figure 4.15, perceived mental demand decreased from the control condition (M = 18.23, SD = 9.29) to the checklist condition (M = 17.42, SD = 8.91) to the predictive display condition (M = 15.61, SD = 6.54). However, no significant difference in the mental demand experienced was observed among participants exposed to the different conditions ( $F(2, 62) = 0.567$ ,  $p = 0.57$ ,  $\omega^2 = -0.013$ ).

*Temporal demand:* The perceived temporal demand experienced by the participants while completing the inspection tasks was measured subjectively using the NASA TLX tool. The



data were tested for normality using the Shapiro-Wilk test. The test was significant for the control condition, the checklist condition and the predictive display condition ( $p < .05$ ). However, the skewness and kurtosis values were within  $\pm 3$ , so normality was assumed for the data. A between-subjects ANOVA was conducted to investigate the effect of type of visualization on the perceived temporal demand reported by the participants. As illustrated in Figure 4.15, perceived temporal demand increased from the control condition ( $M = 8.19$ ,  $SD = 6.57$ ) to the checklist condition ( $M = 8.39$ ,  $SD = 7.99$ ) to the predictive display condition ( $M = 8.73$ ,  $SD = 9.70$ ). However, no significant difference in the temporal demand experienced was observed among participants exposed to the different conditions ( $F(2, 62) = 0.024$ ,  $p = 0.98$ ,  $\omega^2 = -0.031$ ).

*Performance:* The subjective performance perceived by the participants while completing the inspection tasks was measured using the NASA TLX tool. Higher values of performance rating indicate lower perceived performance, and lower values of performance rating indicate higher perceived performance. The perceived performance rating was normally distributed for both the control condition and the checklist condition. However, the test was significant for the predictive display group ( $p = 0.004$ ). As the skewness and kurtosis values were within  $\pm 3$ , normality was assumed for the data.

A between-subjects ANOVA was conducted to investigate the effect of type of visualization on the perceived temporal demand reported by the participants. A significant difference in perceived performance was observed among the participants exposed to the different conditions ( $F(2, 62) = 4.71$ ,  $p = 0.01$ ,  $\omega^2 = 0.102$ ). As illustrated in Figure 4.15, the perceived performance rating increased from the control condition ( $M = 11.65$ ,  $SD =$

6.19) to the predictive display condition ( $M = 8.64$ ,  $SD = 5.40$ ) to the checklist condition ( $M = 6.91$ ,  $SD = 3.40$ ). A post-hoc analysis with Bonferroni correction revealed that the mean increase in perceived performance from the control to the checklist condition ( $-4.74$ , 95% CI  $[-8.58, -0.899]$ ,  $p = 0.01$ ) was statistically significant. However, no statistically significant difference was observed between the mean perceived performance in the predictive display condition and the control condition ( $-3.01$ , 95% CI  $[-6.86, 0.828]$ ,  $p = 0.17$ ), and the checklist condition and the predictive display condition ( $-1.73$ , 95% CI  $[-5.53, 2.07]$ ,  $p = 0.80$ ).

*Effort:* The subjective effort perceived by the participants while completing the inspection tasks was measured subjectively using the NASA TLX tool. Perceived effort was normally distributed for the control, checklist and predictive display groups. A between-subjects ANOVA was conducted to investigate the effect of type of visualization on the perceived effort reported by the participants. As illustrated in Figure 4.15, perceived effort increased from the predictive display condition ( $M = 10.35$ ,  $SD = 6.36$ ) to the control condition ( $M = 10.59$ ,  $SD = 6.89$ ) to the checklist condition ( $M = 11.80$ ,  $SD = 6.81$ ). However, no significant difference in the perceived effort reported was observed among the participants exposed to the different conditions ( $F(2, 62) = 0.299$ ,  $p = 0.74$ ,  $\omega^2 = -0.022$ ).

*Frustration:* The subjective frustration perceived by the participants while completing the inspection tasks was measured subjectively using the NASA TLX tool. Shapiro-Wilk's test was significant for the control condition, the checklist condition and the predictive display condition ( $p > 0.05$ ). However, as the skewness and kurtosis values were within  $\pm 3$ , normality was assumed for the data. The homogeneity of variance assumption was violated

as assessed by Levene’s test ( $p = 0.03$ ); as a result, Welch’s F test was used to test the hypothesis.

A one-way analysis of means not assuming equal variances using Welch’s test was conducted to investigate the effect of type of visualization on the perceived frustration rate reported by the participants. As illustrated in Figure 4.15, perceived frustration increased from the predictive display condition ( $M = 2.17, SD = 2.57$ ) to the control condition ( $M = 2.06, SD = 2.27$ ) to the checklist condition ( $M = 4.76, SD = 5.52$ ). However, no significant difference in the perceived effort reported was observed among participants exposed to different conditions ( $F(2, 38.91) = 2.28, p = 0.12$ ).

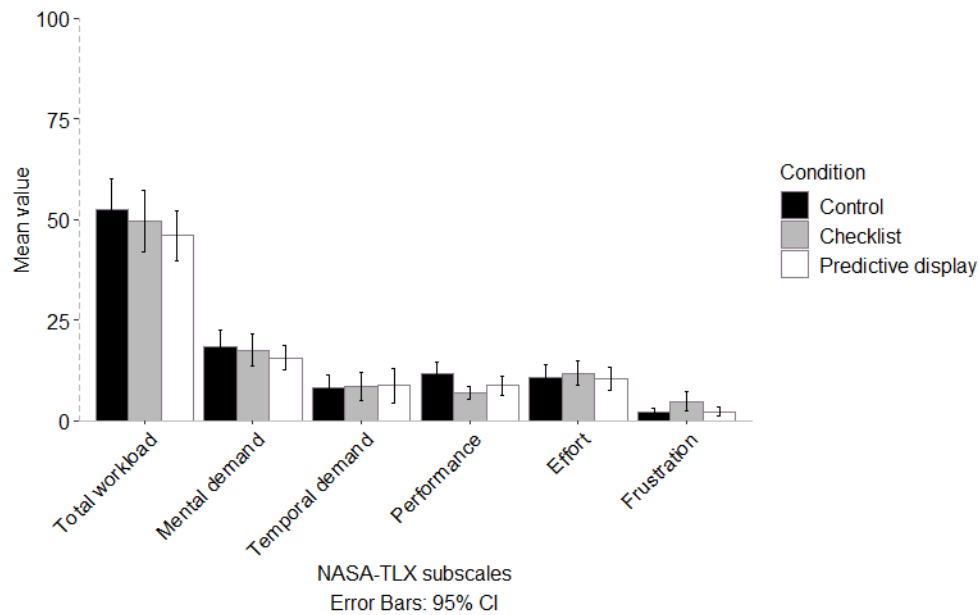


Figure 4.15. Effect of the type of visualization presented on NASA TLX subscales

## DISCUSSION

This study investigated the effect of context-based visual decision aids on improving the SA as well as the performance of windstorm risk engineers using a

convenient sample of 65 civil engineering and construction science and management students. The outcome variables of interest were SAGAT, performance, NASA TLX and time taken to complete the inspection task.

The visual decision aids used in this study were designed based on the user-centered design approach proposed by Endsley (2016). A checklist based decision aid and a predictive display based visual aid were tested in this study. In general, the SA of participants exposed to the predictive display condition and the checklist condition was higher than those who completed the tasks in the control condition, suggesting that the context-based decision aids were effective in supporting the SA requirements of the participants. Additionally, participants had higher Level 1 and Level 3 SA, a result that appears counterintuitive as the latter is more complex and difficult to achieve. However, the participants in this study were able to predict the future state of the infrastructure system leading to significantly higher Level 3 SA than Level 2 SA.

For tasks requiring the participants to inspect the building surroundings and assess potential missile impact water damage, those in the checklist condition and the predictive display condition exhibited a higher Level 2 SA. Past studies have suggested that using procedural checklists could improve the SA of participants. For example, a longitudinal descriptive study investigating the effectiveness of a checklist in improving SA during physician handoffs in a pediatric emergency department reported that the users experienced improved SA with the help of a standardized checklist (Mullan et al., 2015). For the same task in this study, participants in the predictive display condition achieved a higher Level 3 SA compared to other participants. Interactive predictive visualizations showed

participants what if scenarios in the event of a Category 4 hurricane. This knowledge may have contributed to the significantly higher Level 3 SA for those participants as the predictive display may have helped the participants gain a better understanding of the future state of the infrastructure system. The information displayed in the predictive visualization situated around their SA requirements and translated the captured data into a meaningful prediction, resulting in higher SA (Endsley & Connors, 2008). A study investigating the effect of a situation-augmented display on an unmanned aerial vehicle monitoring task suggested that use of such displays may improve the SA of participants. However, this study used time to detect abnormalities as a measure of SA (Lu et al., 2013). Use of measures like SAGAT or SART may be more useful in identifying the actual effect of such visualizations on SA.

A similar trend was observed for tasks requiring the participants to inspect the general condition of a roof underdeck and a rooftop. Participants in the control condition as well as the experimental condition had the same Level 1 SA. Both experienced as well as novice personnel can have the same Level 1 SA. However, integrating this information to comprehend the situation can be challenging for novice engineers (Endsley, 2016). Though we recruited novice participants for this study, those exposed to the experimental condition achieved higher Level 2 and Level 3 SA. Participants also had to take several measurements including fastener spacing and parapet height. A previous study investigating the sensemaking process of windstorm risk engineers revealed that taking dimensions is one of the tasks they frequently forget (Agnisarman et al., 2018). Thus, providing context-based decision aids to support this SA requirement through a checklist

resulted in improved SA. Endsley (2016) suggested that providing assistance for Level 2 SA and Level 3 SA will positively influence SA. The checklist helped participants thoroughly investigate the surroundings through cues and reminders. Additionally, the predictive display processed the Level 1 information and presented details supporting their Level 2 SA and assistance to project the future state of the infrastructure, leading to higher Level 2 and Level 3 SA. For example, the participants had to identify the areas experiencing higher wind pressure based on the presence of parapet and fastener spacing. The predictive display used a heat map to directly show this information as illustrated in Figure 4.4c, leading to higher SA.

The second task additionally required the participants to inspect other roof issues including roof drainage, parapet and the general condition of the roof membrane. Most of the tasks they were asked to complete were related to such obvious issues as the identification of a clogged drain, stagnant water on the rooftop and a membrane tear. However, participants in the checklist condition and the predictive display condition exhibited higher SA. The checklist explicitly asked them to look for these issues, leading to higher probability in correctly answering the SAGAT questions. The predictive display did not have any additional value compared to the checklist condition. Though the checklist showed the participants the future state of the infrastructure in the event of an extreme weather condition, participants found it easier to predict the consequence of some obvious issues like a clogged drain and discontinuous parapet.

For tasks requiring the inspection of the condition of rooftop equipment, participants in the predictive display condition had higher SA compared to participants in

the control condition and the checklist condition. The rooftop housed several improperly attached pieces of equipment. Predicting the specific behavior of some of them and some of their potential impacts was not a straightforward task. For this reason, the checklist alone was not useful enough to complete this task. However, participants in the checklist condition were able to develop a better mental model of the interaction among different components in the event of an extreme weather condition. For example, as illustrated in Figure 4.4d, the dislodged exhaust fan could impact the dock door and damage it. Additionally, the dock door was not impact rated or pressure rated, both of which could exacerbate the damage. Participants in the predictive display were given sufficient information to integrate the available cues to create an accurate mental model, leading to higher SA.

The final task required the participants to inspect the building envelope. For simplicity, participants had to inspect only the envelope of the rooms on the rooftop. Participants in the checklist condition and predictive display condition had higher SA compared to participants in the control condition. Participants in the control condition failed to identify if the windows and dock doors in the rooftop were impact rated or pressure rated. Additionally, they failed to inspect the condition of the EIFS. As participants in the checklist condition and predictive condition were explicitly asked to look for these details, they achieved a higher SA. The SA of participants in the predictive display condition, nonetheless, was not better than that of those in the checklist condition. As some participants suggested, predicting what could happen to a dock door that was not impact

rated is pretty straightforward, suggesting that predictive visualization did not add any additional value beyond the value of checklist.

Though higher SA does not guarantee higher performance, there is only a probabilistic relationship between SA and performance (Endsley & Garland, 2000), meaning participants with higher SA might perform better than participants with lower SA. In this study, participants in the checklist condition performed better than the participants in the control condition. Participants mentioned that the checklist helped them keep track of all the tasks they had to complete. Additionally, it avoided the need to remember the inspection steps in their working memory. Checklists have been used extensively in commercial aviation, research suggesting they provide retrieval cues that help pilots activate the sequence of activities they must perform (Degani & Wiener, 1990; Reason, 1990; Wickens, Hollands, Banbury, & Parasuraman, 2015). Though in the domain of infrastructure risk inspection, errors of omission may not always result in a catastrophe, it could lead to building owners having to pay for a loss that could have been avoided if the inspector had detected the issue in advance. Use of a checklist reduces the chance of an omission error by limiting the reliance on memory (Rosenfield & Chang, 2009), resulting in higher performance. There is sufficient evidence in the literature suggesting improved performance with the use of checklists. For instance, a past study investigating the effectiveness of a checklist for the management of severe local anesthetic systemic toxicity reported improved performance for the group exposed to the checklist in a simulated environment (Neal et al., 2012). In addition to the healthcare domain, checklists are considered one of the simplest tools for reducing human error across different



disciplines including aviation and product manufacturing (Hales & Pronovost, 2006). However, their effectiveness in infrastructure inspection still needs to be investigated more fully.

The participants in the predictive display condition performed significantly better than the participants in the control condition and checklist only condition. For tasks involving the assessment of complex interactions like the one illustrated in Figure 4.4d, the predictive display was particularly useful. Participants exposed to this condition was aware of various direct as well as indirect consequences of a loosely attached exhaust hood. They saw how the fan hood could damage the non-impact rated and the EIFS. However, for much less complicated tasks, checklists alone are sufficient. The predictive display can train novice engineers to probe the scene thoroughly to identify various interactions among different components in the building. Thus, providing an option to activate the predictive display if necessary, will help the novice engineers. Most participants appreciated the predictive display; nonetheless, they suggested that its usefulness is limited to the training phase. However, the significant benefit on expert engineers may be limited as their experience helps them develop an accurate mental model of the future state of the infrastructure system.

Though SAGAT and performance values were found to be higher for participants in the checklist and predictive display condition, the NASA TLX workload measure was not affected by context-based decision aids. Despite the lack of significance in the workload score, the score was lower for the checklist and lowest for the predictive display condition in the sample. Though the use of the checklist did not result in significant

reduction in workload, this finding is promising as it did not place any additional workload on participants. This research is in agreement with the findings from past studies investigating the use of a checklist for pediatric trauma resuscitation (Parsons et al., 2014). Higher workload can have a negative effect on SA as a result of users' inability to integrate and comprehend the cues available in the environment and by requiring the use of already limited working memory (Endsley, 2016; Mahadevan, 2009). Decision aids that reduce the demands on working memory can, in turn, eliminate excessive workload and improve SA. One example of such a decision aid is automation, which has been found to reduce mental demand and thereby improve SA (Endsley, 2016). The predictive display reduced users' mental demand by providing additional support for analyzing and interpreting the data available. It helped the participants integrate seemingly disparate cues and comprehend the data.

Furthermore, the checklist and the predictive display did not have any effect on the time taken to complete the inspection task, indicating that these decision aids did not require participants to spend additional time compared to the control condition. This finding is promising in that using them does not appear to impact the efficiency of the risk engineers. Though the difference in time taken was not significant, participants in the checklist and the predictive display conditions spent more time in the field completing the inspection task, a finding that was not unexpected as those participants completed more required steps than the participants in the control condition.

Though the use of the checklist and predictive display had significant positive effects on performance and SA, it is important to discuss some of the behaviors observed

during the study. Some participants failed to use the checklist effectively. They forgot to open it and had to be reminded to use it from time to time. Participants activated the checklist whenever they wanted. However, keeping them static in the device would eliminate the need for them to remember to activate the checklist. Further, using the checklist can lead to errors of omission it is not comprehensive. The checklist used in this study was designed specifically for the building used in the simulation. In the real world, risk engineers encounter facilities with different roof systems, components and occupancy. Thus, there is a need to develop checklists that can be adapted to the specific condition the engineers will be investigating. It can also be augmented with representative images from real-world situations to improve cue saliency. In addition, using a predictive display can have several consequences as a result of an increased reliability on the system, leading to automation complacency (Wickens et al., 2015); because of increased clue reliance, participants failed to observe other areas despite the fact they may have issues the predictive display failed to highlight.

This phenomenon associated with automation complacency is known as attentional narrowing or tunneling (Wickens et al., 2015). For example, the predictive display showed the potential damage for building flashing in the event of an extreme weather condition. Subsequently, the participants based their conclusion about the flashing solely on the predictive visualization, failing to look for flashing issues in the other locations. Though these did not create any significant issues for the participants' SA or performance for the simplified inspection task used in this study, in a real-world application with complicated inspection tasks, these issues might affect inspectors' performance. Thus, it is important to

study attentional tunneling in detail when designing AI-based decision aids for risk engineers. Multimodal cues based on AI based algorithms can be developed to provide different types of cues such as visual, auditory and haptic to reduce the information processing demands on users (Burke, Prewett, Gray, & Yang, 2006). Multimodal displays exemplify the framework of multiple resources theory by utilizing our capability to process compatible resources at the same time (Burke et al., 2006; Wickens, 2008). Additional studies need to be conducted to investigate the performance of risk engineers while controlling automation assisted technologies such as drones to collect inspection data. Multimodal displays can be used to provide feedback on inspection tasks as well as controlling tasks.

Furthermore, this cross-sectional study investigated the effect of decision aids on the SA and performance immediately after watching the training video and completing the training scenario. The retention effect or the training value of these decision aids is still unknown. Further follow-up studies need to be conducted without these decision aids to investigate the retention effect of these aids on user performance and SA.

This study is not without limitations. One of the limitations of this study is the use of convenient sampling. This study recruited civil engineering and construction science and management junior/senior/graduate students. Furthermore, the performance questionnaire used in this study is not a validated questionnaire. It was developed based on the inspection tasks and validated by the subject matter expert.

## CONCLUSION

This study investigated the effect of various context-based visualization strategies on the performance and situation awareness of participants using a simulated environment and a convenient sample of civil engineering and construction science and management students. The findings suggest that the participants in the checklist and predictive display condition had higher performance and SA compared to the participants in the control condition. The use of context-based decision aids had a positive effect by reducing the reliance on memory. Additionally, the decision aids helped users integrate the cues available to make sense of the environment. More specifically, the checklist alone was sufficient for some tasks including the inspection of obvious issues like roof ponding, cracking and clogged drainage. However, for other tasks involving the identification of the interaction among different components in the building, the predictive display provided additional benefits. This finding is important to consider when selecting decision aids for infrastructure inspection. By providing predictive visualization for only complicated tasks, the computational demands may also be reduced. Additionally, as suggested by some participants, the digital checklist can be augmented with pictures of issues to help users identify them in the building.

The results suggest that the use of checklist and predictive display might result in reduced workload. However, the study needs to be conducted with more participants to identify the effect of these decision aids on the SA and performance of risk engineers. Additionally, the decision aids need to be tested with the actual users in real inspection scenarios to investigate the effect of these aids on the SA and performance in a real-world

situation. In addition, we noticed that use of these decision aids can lead to attentional tunneling. The potential of using additional decision aids such as haptic cues based on AI algorithms need to be investigated in detail in future research endeavors. Finally, the potential of these decision aids on training risk engineers needs to be investigated further to learn how they can be used to impart procedural knowledge as well as to improve SA. Follow-up studies need to be conducted to investigate if the decision aids have any long-term effect on the SA requirements of participants.

## CHAPTER FIVE

# THE TRANSFER OF THE TRAINING EFFECT OF CONTEXT-BASED VISUAL DECISION AIDS ON THE SITUATION AWARENESS OF WINDSTORM RISK ENGINEERS

## INTRODUCTION

A windstorm risk inspection survey, the process of assessing the wind vulnerability of a building to limit damages in the event of extreme weather conditions (Smith, 2011), benefits both the owners as well as the insurance companies who use the findings from these surveys to improve their underwriting process. However, the accuracy of this process depends on the skillset of the engineer conducting the inspection (Agnisarman et al., 2018). This situation is further impacted by the lack of a standard protocol combined with individual differences, resulting in disparities in reports produced by different field engineers (Agnisarman et al., 2018). One approach for addressing this situation is through appropriate training. Necessary for ensuring the adequate performance of any employee (Olaniyan & Ojo, 2008), training is especially important for windstorm risk engineers as this process involves developing a mental model of the future state of infrastructure (Agnisarman et al., 2018).

The windstorm risk inspection process requires risk engineers to assess the current state of the infrastructure as well as develop a mental model for its future state in the event of extreme weather conditions. However, this task can be challenging for novice engineers as experience is an important factor directly predicting the accuracy of the risk inspection task. Previous qualitative research investigating the sensemaking process of windstorm risk

engineers observed a difference in the sensemaking process of novice and expert engineers. Experienced engineers tend to critically evaluate the information before making a decision, evaluating multiple potential reasons for any issues they observe before proposing a recommendation. However, novice engineers might overlook some of the important information and make decisions without thoroughly evaluating the environment (Agnisarman et al., 2018). Automation assisted technologies and Artificial Intelligence (AI) have been used by researchers and practitioners, both novice and experienced engineers, to improve the accuracy of the infrastructure inspection process (Agnisarman et al., 2019). However, operator performance in such systems is mediated by vigilance decrements, complacency and loss of situation awareness (Endsley & Kiris, 1995; Endsley, 1999).

Situation awareness (SA) is the perception of cues in the environments (Level 1), comprehension of the current state of the system (Level 2) and projection of the future state of the system (Level 3) (Endsley, 1995b). A previous study exploring the possibility of using context-based visual decision aids to support the SA of windstorm risk engineers (Chapter 4) investigated the use of a standardized checklist as well as an AI based predictive visualization on the SA and the performance of windstorm risk engineers. However, only limited research exists investigating the long-term effect of such visual decision aids in their absence, or their retention effect. Pugh, Wickens, Herdener, Clegg, and Smith (2018) identified the limitations of this existing research as the lack of evidence on the transfer of the training effect of such visual decision aids. In fact, past research has found that visualizations offering support to the users did not have any effect when they



were removed (Pugh et al., 2018; Wickens, Merwin, & Lin, 1994). However, only limited research exists in the context of windstorm infrastructure inspection investigating the transfer of training effect of visual decision aids.

A continuation of a previous study investigating the impact of checklist based and predictive display based decision aids on the SA and performance during windstorm risk inspection tasks (Chapter 4), this study investigated the transfer of training effect of these aids. A past study investigating the use of a checklist for emergency department shift handoffs reported an improved perceived quality of care and team communication (Mullan, Macias, Hsu, Alam, & Patel, 2015). However, thus far no research has extended this investigation into study the effectiveness of checklist-based training materials for infrastructure inspection.

In the civil and construction engineering domain, researchers have recently begun using Virtual Reality (VR) based training methods (Vahdatikhaki et al., 2019). For example, one study investigated the effectiveness of VR based and 360-degree panoramic view based training methods for hazard identification in construction sites (Eiris, Gheisari, & Esmaeili, 2020). Researchers have also investigated the possibility of integrating an affective human-machine interface in VR based crane training simulator, the results indicating a higher perceived performance with the affective interface (Rezazadeh, Wang, Firoozabadi, & Hashemi Golpayegani, 2011). Another study investigated the use of real-time location tracking based immersive data visualization technologies for construction worker training and education (Teizer, Cheng, & Fang, 2013). However, none of the

studies has investigated the effectiveness of such immersive visualization technologies for training infrastructure inspectors.

In this research we investigated the transfer of training effect of checklist based and predictive display based visual decision aids on SA and performance, asking the following questions:

#### *Research questions*

- How do context-based decision aids help with knowledge retention?
- How does the SA of participants change over time when the context-based decision aids are removed?
- How does the performance of participants change over time when the context-based decision aids are removed?
- How does the workload change over time when the context-based decision aids are removed?

To answer these research questions, following hypotheses were tested:

#### *Hypotheses*

- Participants exposed to the context-based decision aids in the first trial will have higher SA when the decision aids are removed in the second trial.
- Participants exposed to the context-based decision aids in the first trial will perform better when the decision aids are removed in the second trial.
- The absence of decision aids will not have any effect on the workload experienced by the participants.

## METHOD

### *Study sample*

This study recruited 65 junior/senior and graduate level students with civil engineering or construction backgrounds as a proxy for novice risk engineers with minimal experience in risk inspection. However, two participants were removed from the analysis as they did not complete the follow-up session, meaning analysis used only 63 participants, ranging from 20 to 41 years old ( $M=23.32$ ,  $SD=3.36$ ). More demographic information about the participants can be found in Table 5.1.

Table 5.1. Demographic characteristics of the participants

Variable (N = 63)	N	%
<b>Gender</b>		
Female	13	21
Male	50	79
<b>Race</b>		
White	38	60
Asian	17	27
Black/African American	5	8
Other	3	5
<b>Major</b>		
Civil Engineering	53	84
Construction Science	10	16
<b>Degree Pursuing</b>		
Undergraduate	37	59

Graduate	15	24
Doctorate	11	17

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### *Apparatus*

A desktop computer with an Intel(R) Xeon(R) CPU E5-1620 v4 processor and a Quadro FX 5800 GPU was used to run the simulations of the windstorm risk survey. The display used was an LG ultralight monitor with a diagonal dimension of 38.8". A Unity game engine was used to develop the simulations for this study (Unity, 2005). The demographic survey, SAGAT questionnaire and post surveys were administered through Qualtrics research suite using a laptop computer (Qualtrics, 2005).

### *Simulation*

The details of the simulation used in the first study can be found in Chapter 4. The follow-up study used a simulation of a hotel building located on the Atlantic Coast. The exposure category used in this study was Exposure D with a flat unobstructed area exposed to wind flowing over open water ("Windexpo," 2019). Figure 5.1 shows four screenshots from the simulation used in the follow-up study. This building also had equipment that could be potential missiles on the rooftop.

### *Stimuli*

The decision aids used in the first study are explained in Chapter 4. Participants completed the inspection tasks in the follow-up study without decision aids.

### *Independent variables*

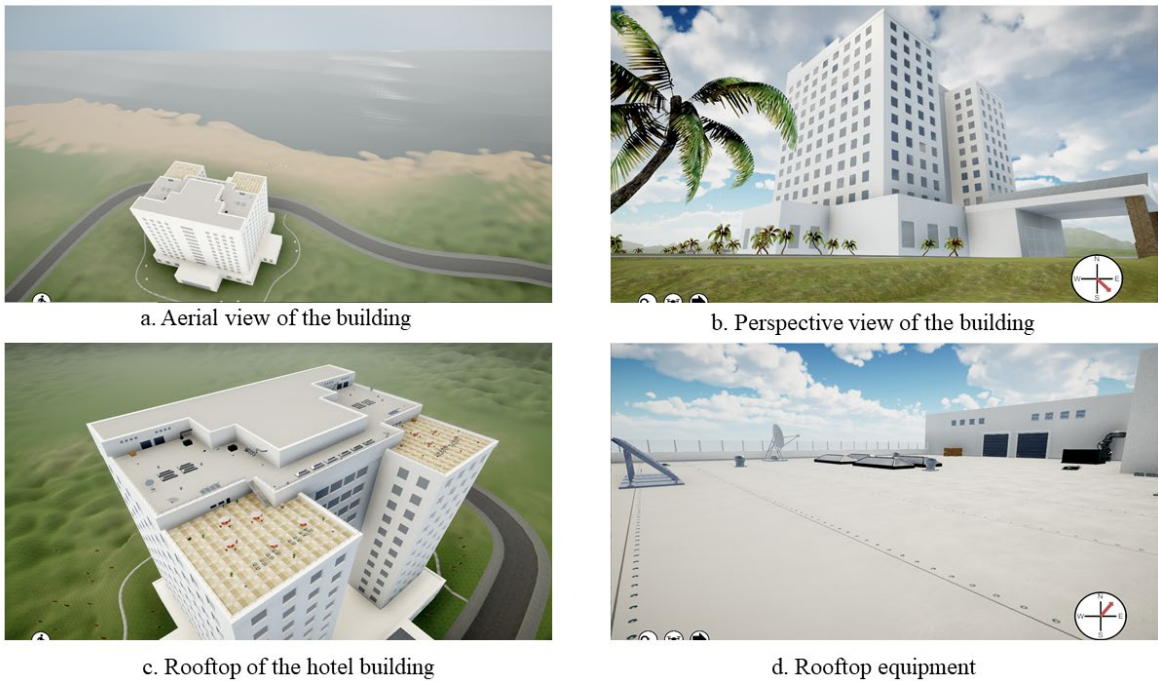


Figure 5.1. The hotel simulation used in the follow up study

*Type of context-based visual aids presented (3 levels):* This variable was presented in 3 levels: 1) predictive display condition, 2) checklist condition and 3) control condition. In the first study, only participants in the control condition did not have any context-based decision aids; in this follow-up study, all participants completed the inspection tasks without decision aids.

*Trial (2 levels):* Participants completed the inspection task twice. 1) Trial 1 and 2) Trial 2. The follow-up inspection task was completed a week after the first study without any decision aids.

*Dependent variables*

*Situation awareness:* Situation awareness was measured using the Situation Awareness Global Assessment (SAGAT) technique (Endsley, 1995b). This objective method freezes

the simulation at random times to administer the questionnaire. In this study the simulation was frozen at five predefined time points as the simulated environment was not highly dynamic. A similar approach was adopted by researchers investigating the SA of medical trainees (Gardner et al., 2017). All but one set of SAGAT queries were administered following the completion of each inspection task. One set was administered during one of the tasks. The SA requirements of windstorm risk engineers were identified through detailed one-on-one interviews. The SAGAT queries were then developed to match these SA requirements. Each trial included 5 sets of SAGAT queries. The SAGAT questions used in this study can be found in Appendix I.

*Workload:* The workload experienced by the participants was measured using The National Aeronautics and Space Administration Task Load Index (NASA-TLX). This is a multidimensional instrument used to measure the workload experienced (Hart, 2006; Hart & Staveland, 1988).

*Performance:* Participant performance was assessed using a performance questionnaire. The performance questionnaire was developed based on the tasks used in the study. The questionnaire was then validated by the SME. This questionnaire can be found in Appendix J. The time taken to complete the inspection task was not considered because the simulation used was different in both studies.

#### *Procedure*

*First study (Trial 1):* The procedure for the first study can be found in Chapter 4.

*Follow up study (Trial 2):* Participants were asked to return after a week for a follow-up session. They completed the inspection task using the hotel simulation (Figure 5.1) with

no context based decision aids for both conditions, the control and the experimental. The simulation froze at five preselected time points to administer the SAGAT questionnaire. Upon completing the inspection task, participants answered performance as well as NASA TLX questionnaires, followed by a retrospective think-aloud session in which they discussed their experiences completing the inspection tasks in the simulation. Those exposed to the checklist or predictive display condition in the initial study were also asked how these decision aids helped them with the inspection task. Further, the participants were asked to compare their first and follow-up study experiences.

#### *Data analysis*

R language for statistical computing was used for the data analysis (R Core Team, 2019). The multilevel modeling technique was used to analyze the data collected using a mixed design. The study condition was the between subjects variable and the trial was the within subjects variable. The SAGAT responses were coded as 0 (for incorrect answer) and 1 (for correct answers). Since there were some differences in the SAGAT questions used in the first and second studies, the data were not analyzed using logistic regression model. SAGAT responses for each freeze were consolidated, and a percentage score for each condition per each freeze was calculated. Outliers were identified using standardized residuals. Below are the equations used for the multilevel modeling.

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij} \quad (5.1)$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{1j} \quad (5.2)$$

where

- $\beta_{0j}$ =intercept that varies
- $\beta_{1j}$ =slope
- $e_{ij}$ =deviation from group
- $\gamma_{00}$ =fixed effect
- $\gamma_{01}$ =slope for the relationship between the DV  $Y_{ij}$  and level 2 IV  $Z$
- $Z$ =level 2 IV
- $u_{ij}$ =random effect

## RESULTS

### *SAGAT*

The SAGAT responses were coded as zeros (incorrect answers) and ones (correct answers) and then summed to obtain a cumulative SAGAT score for each freeze. The percentage of correct responses was calculated for each freeze and used as the dependent variable in the data analysis. No extreme data points were identified as assessed by the deviance value. The following sections detail the analysis of each of the SAGAT freezes separately.

*Inspection of surroundings (SAGAT 1):* This task involves inspecting the surroundings of the building to identify any flood exposure or potential missiles. This task required the participants to walk around the building to identify any issues; they had the opportunity to use a drone to identify the wind exposure level of the building. Table 5.2 illustrates the details of the iterative modeling.



In the final model, the main effect of the type of visualization was significant with  $\Delta\chi^2 = 28.72$  and  $p < 0.001$ . However, the main effect of trial was not significant ( $\Delta\chi^2 = 3.17$ ,  $p = 0.07$ ). The interaction between the type of visualization and the study trial was significant ( $\Delta\chi^2 = 15.75$ ,  $p = 0.0004$ ). Further analysis was conducted to investigate the nature of this interaction. As illustrated in Figure 5.2, the SA was significantly higher in Trial 2 compared to Trial 1 for the control condition ( $b = 19.04$ ,  $SE = 4.38$ ,  $95\%CI [5.66, 32.43]$ ,  $p < 0.001$ ). However, no significant difference in SA was observed between the first and second trials for participants in the checklist condition ( $b = -1.99$ ,  $SE = 4.27$ ,  $95\%CI [-15.05, 11.07]$ ,  $p = 0.99$ ) and the predictive display condition ( $b = -2.27$ ,  $SE = 4.17$ ,  $95\%CI [-15.03, 10.49]$ ,  $p = 0.99$ ). The mean values can be found in Table 5.3.

Table 5.2. Model summary for iterative model building for inspection of surroundings (SAGAT 1)

Variable	Model1			Model2, $R^2 = 0.02$ , $p = 0.10$			Model3, $R^2 = 0.22$ , $p < 0.001$			Model4, $R^2 = 0.32$ , $p = 0.0004$		
	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper
Constant	80.39 (1.50)	77.41	83.37	78.09 (2.05)	74.03	82.16	67.73 (2.65)	62.51	72.95	60.50 (3.10)	54.46	66.54
Trial												
Trial 2				4.59 (2.78)	-0.93	10.11	4.59 (2.60)	-0.53	9.71	19.05 (4.38)	10.50	27.59
Experimental condition (type of visualization)												
Checklist							12.79 (3.23)	6.44	19.15	23.31 (4.32)	14.87	31.75
Predictive display							17.48 (3.19)	11.19	23.76	28.14 (4.28)	19.79	36.48
Interaction between condition and trial												
Checklist: trial 2										-21.04 (6.11)	-32.98	-9.10
Predictive display: trial 2										-21.32 (6.05)	-33.12	-9.51

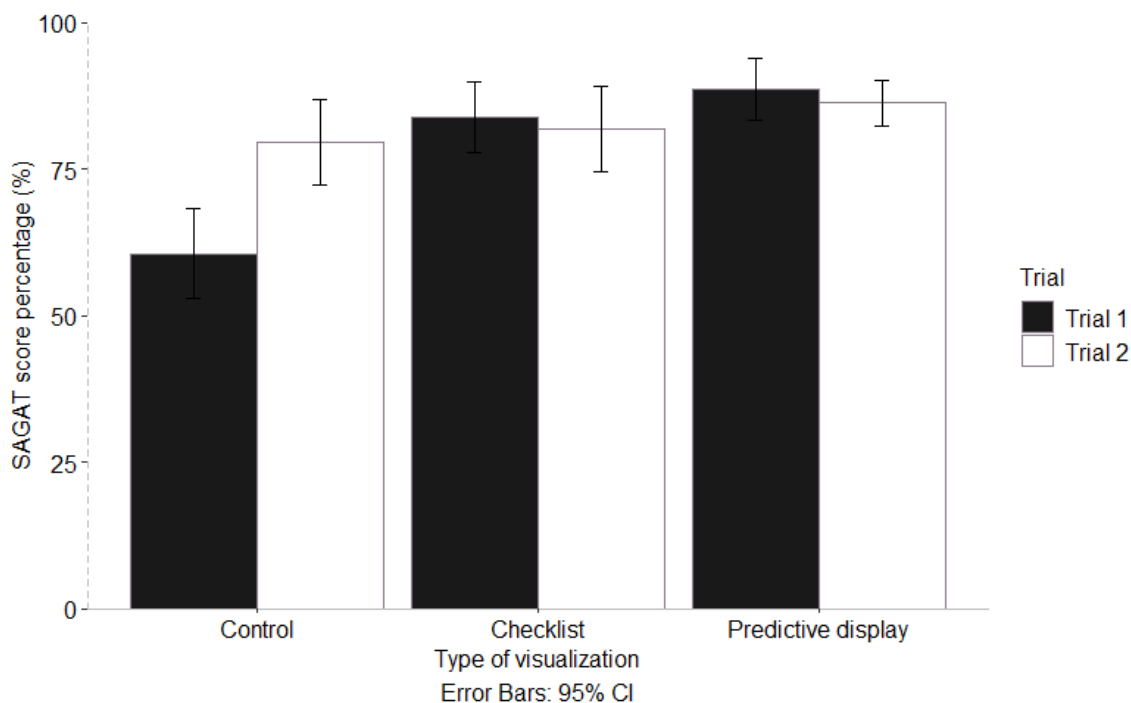


Figure 5.2. Interaction effect of trial and type of visualization (inspection of surroundings — SAGAT 1)

Table 5.3. Mean and SD of percentage of correct SAGAT responses for inspection of surroundings task (SAGAT 1)

		Type of visualization		
		Control	Checklist	Predictive display
Trial	Trial 1	60.50 (16.38)	83.81 (13.22)	88.64 (12.07)
	Trial 2	79.55 (15.57)	81.82 (16.00)	86.36 (8.76)

*Inspection of underdeck and rooftop (SAGAT 2):* This step involved the inspection of underdeck and rooftop. More specifically, the participants were asked to inspect the condition of underdeck including if the fastener rows were parallel or perpendicular to the roof rib, the fastener dimensions, the weld spacing and the fastener dimensions on the rooftop. The simulation was frozen after completing these tasks. Table 5.4 illustrates the details of the iterative modeling.

Table 5.4. Model summary for iterative model building for inspection of underdeck and rooftop (SAGAT 2)

Variable	Model1			Model2, $R^2 = 0.05$ , $p = 0.0001$			Model3, $R^2 = 0.36$ , $p < 0.001$			Model4, $R^2 = 0.39$ , $p = 0.01$		
	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper
Constant	60.80 (2.65)	55.53	66.07	66.27 (2.98)	60.35	72.19	48.82 (3.91)	41.13	56.51	43.13 (4.34)	34.66	51.59
Trial												
Trial 2				-10.94 (2.71)	-16.32	-5.56	-10.94 (2.73)	-16.32	-5.56	0.45 (4.55)	-8.44	9.33
Experimental condition (type of visualization)												
Checklist							18.05 (5.12)	7.97	28.11	25.92 (6.06)	14.09	37.75
Predictive display							32.75 (5.06)	22.79	42.71	41.53 (5.99)	29.83	53.23
Interaction between condition and trial												
Checklist: trial 2										-15.75 (6.36)	-28.17	-3.33
Predictive display: trial 2										-17.57 (6.29)	-29.85	-5.29

In the final model, the main effect of the type of visualization was significant with  $\Delta\chi^2 = 32.96$  and  $p < 0.001$ . The main effect of trial was also significant ( $\Delta\chi^2 = 14.69$ ,  $p < 0.001$ ), and the interaction between the type of visualization and the study trial was significant ( $\Delta\chi^2 = 9.03$ ,  $p = 0.01$ ). Further analysis was conducted to study the nature of this interaction. As illustrated in Figure 5.3, no significant difference in SA was observed between the first and second trials for participants in the control condition ( $b = 0.45$ ,  $SE = 4.55$ ,  $95\%CI [-13.47, 14.37]$ ,  $p = 0.99$ ). However, the SA was significantly lower for Trial 2 for participants in the checklist condition ( $b = -15.31$ ,  $SE = 4.44$ ,  $95\%CI [-28.89, -1.72]$ ,  $p = 0.01$ ) and the predictive display condition ( $b = -17.13$ ,  $SE = 4.34$ ,  $95\%CI [-30.40, -3.86]$ ,  $p = 0.003$ ). The mean values can be found in Table 5.5.

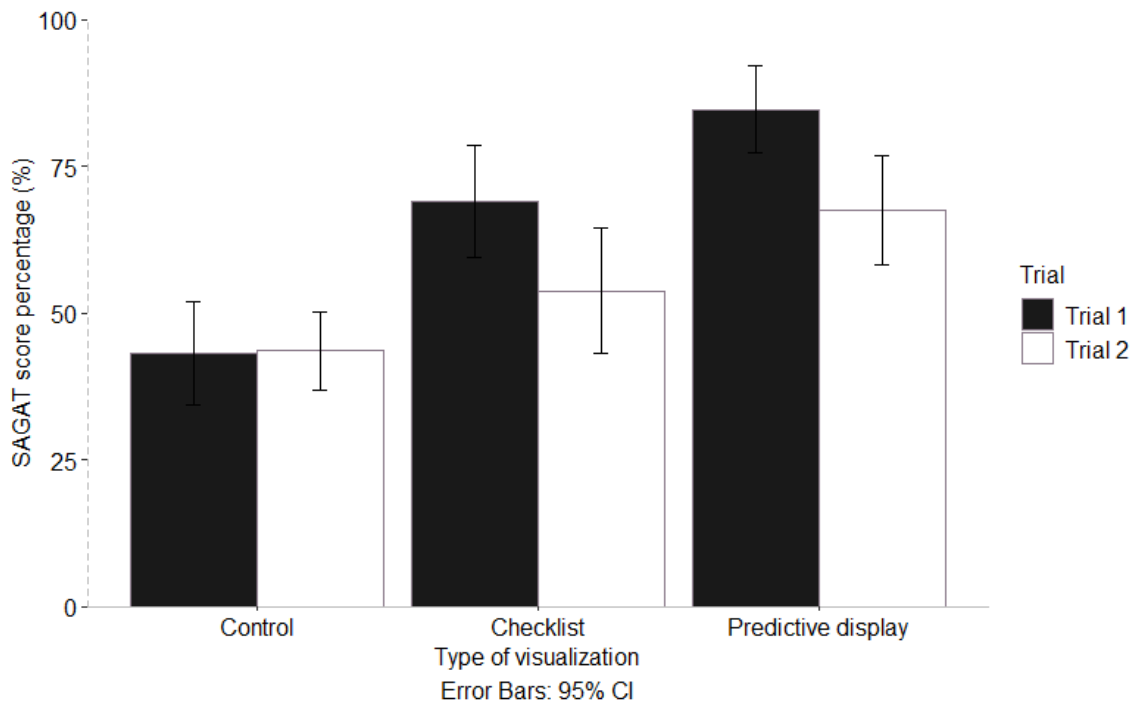


Figure 5.3. Interaction effect of trial and type of visualization (inspection of underdeck and rooftop — SAGAT 2)

Table 5.5. Mean and SD of percentage of correct SAGAT responses for inspection of underdeck and rooftop (SAGAT 2)

		Type of visualization		
		Control	Checklist	Predictive display
	Trial 1	43.13 (18.79)	69.05 (20.77)	84.66 (16.78)
Trial	Trial 2	43.57 (14.27)	53.74 (23.43)	67.53 (20.76)

*Inspection of underdeck and rooftop continuation (SAGAT 3):* This continuation of the inspection of underdeck and rooftop involved inspecting the general condition of the rooftop including identifying any tears, ponding and blocked drains. Additionally, the participants had to measure the height of the parapet wall and inspect its general condition. The simulation was frozen at the end of this task to administer the third set of the SAGAT questions. Table 5.6 illustrates the iterative model summary.

In the final model, the main effect of the type of visualization was significant with  $\Delta\chi^2 = 23.30$  and  $p < 0.001$ . The main effect of trial was also significant ( $\Delta\chi^2 = 4.49$ ,  $p = 0.03$ ), and the interaction between the type of visualization and the study trial was significant ( $\Delta\chi^2 = 10.57$ ,  $p = 0.005$ ). Further analysis was conducted to investigate the nature of this interaction. As illustrated in Figure 5.4, no significant difference in SA was observed between the first and second trials for participants in the control condition ( $b = 7.18$ ,  $SE = 5.03$ ,  $95\%CI [-8.21, 22.57]$ ,  $p = 0.99$ ), the checklist condition ( $b = -11.52$ ,  $SE = 4.91$ ,  $95\%CI [-26.54, 3.50]$ ,  $p = 0.34$ ) and the predictive display condition ( $b = -14.13$ ,  $SE = 4.80$ ,  $95\%CI [-28.81, 0.54]$ ,  $p = 0.07$ ). The mean values can be found in Table 5.7.

Table 5.6. Model summary for iterative model building for inspection of underdeck and rooftop continuation (SAGAT 3)

Variable	Model1			Model2, R <sup>2</sup> = 0.03, p = 0.034			Model3, R <sup>2</sup> = 0.21, p<0.0001			Model4, R <sup>2</sup> = 0.27, p = 0.005		
	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper
Constant	71.36 (1.94)	67.50	75.21	74.60 (2.47)	69.71	79.49	62.84 (3.27)	56.40	69.28	56.00 (3.85)	48.48	63.52
Trial												
Trial 2				-6.49 (3.03)	-12.51	-0.48	-6.49 (3.06)	-12.51	-0.48	7.18 (5.03)	-2.65	17.00
Experimental condition (type of visualization)												
Checklist							13.70 (4.04)	5.74	21.66	23.05 (5.38)	12.54	33.56
Predictive display							20.62 (4.00)	12.75	28.48	31.27 (5.32)	20.88	41.67
Interaction between condition and trial												
Checklist: trial 2										-18.70 (7.03)	-32.43	-4.97
Predictive display: trial 2										-21.31 (6.70)	-34.89	-7.74

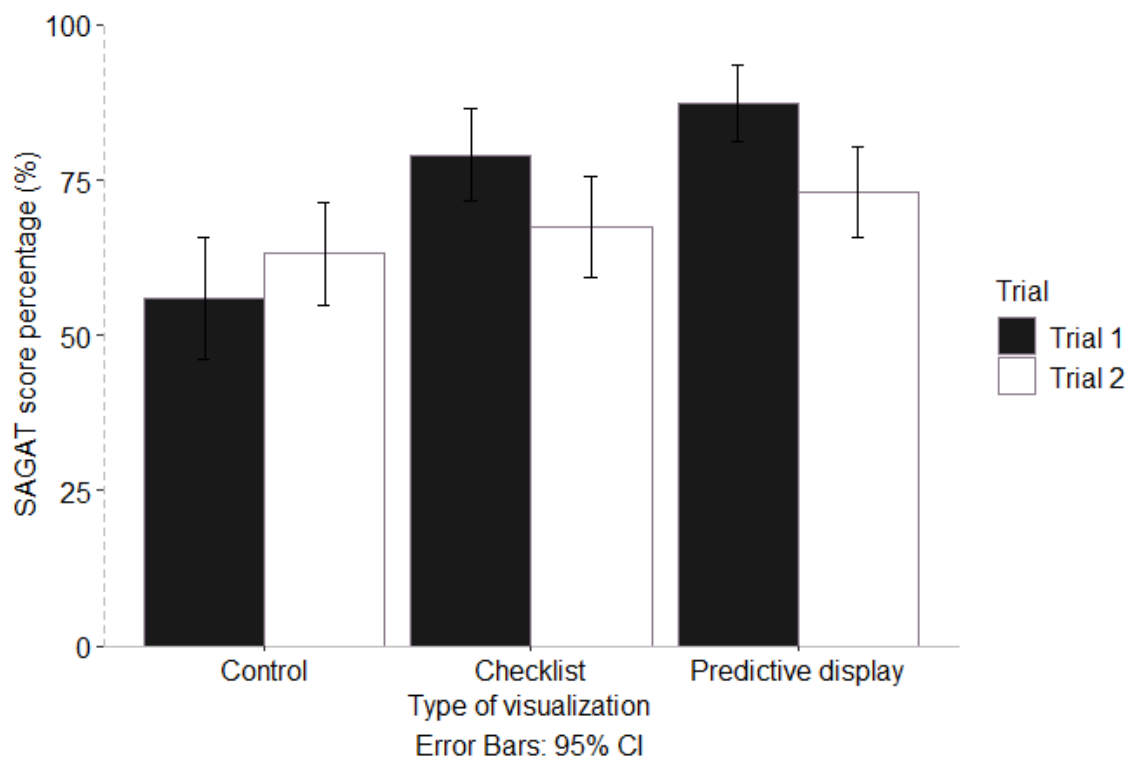


Figure 5.4. Interaction effect of trial and type of visualization (inspection of underdeck and rooftop continuation — SAGAT 3)

Table 5.7. Mean and SD of percentage of correct SAGAT responses for inspection of underdeck and rooftop continuation (SAGAT 3)

		Type of visualization		
		Control	Checklist	Predictive display
Trial	Trial 1	56.00 (20.88)	79.05 (16.40)	87.27 (13.86)
	Trial 2	63.18 (17.57)	67.53 (17.85)	73.14 (16.47)

*Inspection of rooftop equipment (SAGAT 4):* This task required the participants to inspect the general condition of rooftop equipment, including identifying how various pieces were fastened to the rooftop and what could happen to them in the event of extreme weather conditions. Upon completing this task, participants completed the fourth set of SAGAT questions. Table 5.8 illustrates the iterative model summary.



Table 5.8. Model summary for iterative model building for inspection of rooftop equipment (SAGAT 4)

Variable	Model1			Model2, $R^2 = 0.02$ , $p = 0.04$			Model3, $R^2 = 0.21$ , $p < 0.001$			Model4, $R^2 = 0.24$ , $p = 0.06$		
	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper
Constant	67.03 (2.42)	62.22	71.85	70.83 (3.03)	64.82	76.85	59.43 (4.10)	51.37	67.48	53.75 (4.85)	44.29	63.21
Trial												
Trial 2				-7.60 (3.64)	-14.81	-0.40	-7.61 (3.66)	-14.81	-0.40	3.75 (6.27)	-8.49	15.99
Experimental Condition (type of visualization)												
Checklist							8.36 (5.11)	-1.71	18.44	14.70 (6.77)	1.49	27.92
Predictive display							24.68 (5.06)	14.72	34.64	34.89 (6.69)	21.82	47.95
Interaction between condition and trial												
Checklist: trial 2										-12.68 (8.76)	-29.78	4.42
Predictive display: trial 2										-20.42 (8.66)	-37.33	-3.50

In the final model, the main effect of the type of visualization was significant with  $\Delta\chi^2 = 21.54$  and  $p < 0.001$ . The main effect of trial was also significant ( $\Delta\chi^2 = 4.30$ ,  $p = 0.04$ ). The interaction between the type of visualization and the study trial was marginally significant ( $\Delta\chi^2 = 5.64$ ,  $p = 0.06$ ). Further analysis was conducted to examine the nature of this interaction. As illustrated in Figure 5.5, no significant difference in SA was observed between the first and the second trials for participants in the control condition ( $b = 3.75$ ,  $SE = 6.27$ ,  $95\%CI [-15.42, 22.92]$ ,  $p = 0.99$ ), the checklist condition ( $b = -8.93$ ,  $SE = 6.12$ ,  $95\%CI [-27.64, 9.78]$ ,  $p = 0.99$ ) and the predictive display condition ( $b = -16.67$ ,  $SE = 5.98$ ,  $95\%CI [-34.95, 1.61]$ ,  $p = 0.1$ ). The mean values can be found in Table 5.9.

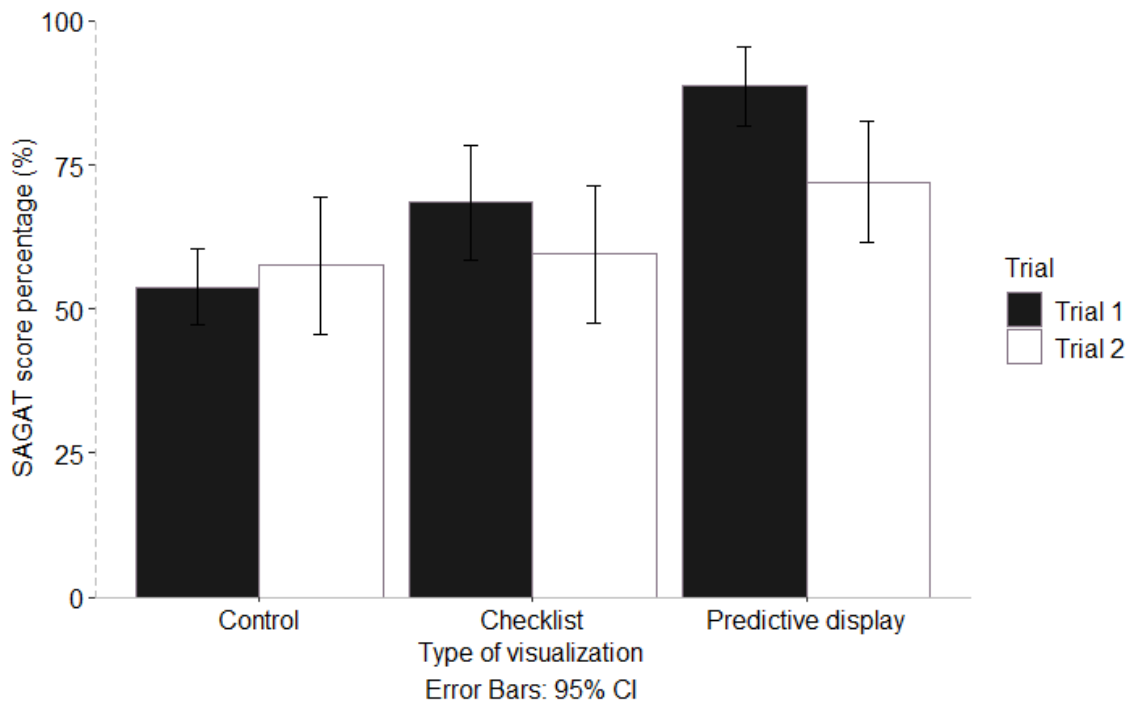


Figure 5.5. Interaction effect of trial and type of visualization (inspection of rooftop equipment — SAGAT 4)

Table 5.9. Mean and SD of percentage of correct SAGAT responses for inspection of rooftop inspection (SAGAT 4)

		Type of visualization		
		Control	Checklist	Predictive display
	Trial 1	53.75 (14.11)	68.45 (21.87)	88.64 (15.39)
Trial	Trial 2	57.50 (25.63)	59.52 (26.13)	71.97 (23.79)

*Inspection of envelope (SAGAT 5):* This task involved the inspection of the building envelope including the doors, windows and the EIFS. In an actual risk inspection scenario, engineers inspect the envelope of the entire building. However, in this study, this task was simplified to include the inspection of the windows, dock doors and the EIFS of the rooms on the rooftop. The query included questions about the general condition of these components and the possible damage they could sustain. Table 5.10 illustrates the iterative model summary.

In the final model, the main effect of the type of visualization was significant with  $\Delta\chi^2 = 17.42$  and  $p = 0.0002$ . The main effect of trial was also significant ( $\Delta\chi^2 = 7.68$ ,  $p = 0.006$ ). The interaction between the type of visualization and the study trial was marginally significant ( $\Delta\chi^2 = 8.84$ ,  $p = 0.01$ ). Further analysis was conducted to explore the nature of this interaction. As illustrated in Figure 5.6, a significant difference in SA was observed between the first and second trials for participants in the control condition ( $b = 19.37$ ,  $SE = 4.94$ ,  $95\%CI [4.26, 34.49]$ ,  $p = 0.003$ ). However, no significant difference in SA was observed between Trial 1 and Trial 2 for participants in the checklist condition ( $b = 7.44$ ,  $SE = 6.74$ ,  $95\%CI [-13.17, 28.95]$ ,  $p = 0.99$ ) and the predictive display condition ( $b = -1.13$ ,  $SE = 4.71$ ,  $95\%CI [-15.55, 13.27]$ ,  $p = 0.99$ ). The mean values can be found in Table 5.11.

Table 5.10. Model summary for iterative model building for inspection of building envelope (SAGAT 5)

Variable	Model1			Model2, R <sup>2</sup> = 0.03, p = 0.006			Model3, R <sup>2</sup> = 0.21, p = 0.0002			Model4, R <sup>2</sup> = 0.24, p = 0.01		
	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper
Constant	72.22 (2.63)	66.99	77.45	68.06 (3.02)	62.07	74.04	54.90 (4.37)	46.30	63.49	49.37 (4.82)	39.56	58.79
Trial												
Trial 2				8.33 (2.94)	2.50	14.16	8.33 (2.96)	2.50	14.16	19.37 (4.94)	9.72	29.03
Experimental condition (type of visualization)												
Checklist							13.26 (5.74)	1.96	24.56	19.08 (6.74)	5.92	32.24
Predictive display							25.03 (5.68)	13.85	36.21	35.28 (6.67)	22.27	48.30
Interaction between Condition and trial												
Checklist: trial 2										-11.64 (6.91)	-25.12	1.85
Predictive display: trial 2										-20.51 (6.83)	-33.85	-7.18

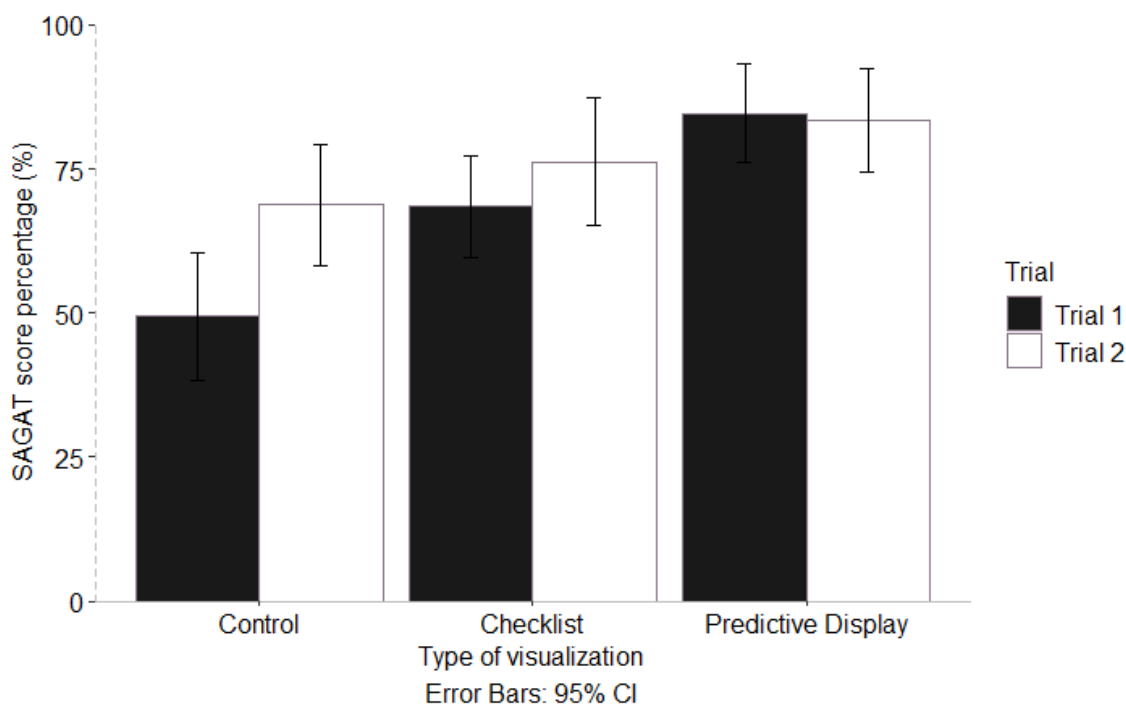


Figure 5.6. Interaction effect of trial and type of visualization (inspection of building envelope — SAGAT 5)

Table 5.11. Mean and SD of percentage of correct SAGAT responses for inspection of building envelope (SAGAT 5)

		Type of visualization		
		Control	Checklist	Predictive display
Trial	Trial 1	49.37 (23.46)	68.45 (19.61)	84.66 (19.26)
	Trial 2	68.75 (22.40)	76.19 (24.33)	83.52 (20.19)

### *Performance*

Participants' performance was measured using a questionnaire administered at the end of each trial. Their responses were graded, and a cumulative score was calculated. A percentage of right responses was calculated for both Trial 1 and Trial 2. The data were analyzed using a linear multilevel approach. The summary of the multilevel modeling can be seen in Table 5.12.

Table 5.12. Model summary for iterative model building for performance data

Variable	Model1			Model2, R <sup>2</sup> = 0.05, p = 0.0003			Model3, R <sup>2</sup> = 0.23, p = 0.0002			Model4, R <sup>2</sup> = 0.26, p = 0.003		
	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper
Constant	69.59 (1.51)	66.58	72.59	66.67 (1.70)	63.29	70.04	59.40 (2.49)	54.52	64.29	56.25 (2.70)	50.98	61.52
Trial												
Trial 2				5.84 (1.55)	2.76	8.92	5.84 (1.56)	2.76	8.92	12.15 (2.56)	71.5	17.15
Experimental condition (type of visualization)												
Checklist							6.72 (3.30)	0.23	13.21	9.82 (3.77)	2.45	17.19
Predictive display							14.38 (3.26)	7.96	20.79	20.45 (3.73)	13.17	27.74
Interaction between Condition and trial												
Checklist: trial 2										-6.20 (3.58)	-13.18	0.78
Predictive display: trial 2										-12.15 (3.54)	-19.06	-5.25

In the final model, the main effect of the type of visualization was significant with  $\Delta\chi^2 = 17.51$  and  $p = 0.0002$ . The main effect of trial was also significant ( $\Delta\chi^2 = 12.96$ ,  $p = 0.0003$ ). The interaction between the type of visualization and the study trial was marginally significant ( $\Delta\chi^2 = 11.31$ ,  $p = 0.003$ ). Further analysis was conducted to examine the nature of this interaction. As illustrated in Figure 5.7, a significant difference in SA was observed between the first and second trials for the participants in the control condition ( $b = 12.15$ ,  $SE = 2.56$ ,  $95\%CI [4.32, 19.98]$ ,  $p = 0.0002$ ). However, no significant difference in SA was observed between Trial 1 and Trial 2 for participants in the checklist condition ( $b = 5.95$ ,  $SE = 2.50$ ,  $95\%CI [-1.69, 13.59]$ ,  $p = 0.31$ ) and the predictive display condition ( $b < 0.001$ ,  $SE = 2.44$ ,  $95\%CI [-7.46, 7.46]$ ,  $p = 0.99$ ). The mean values can be found in Table 5.13.

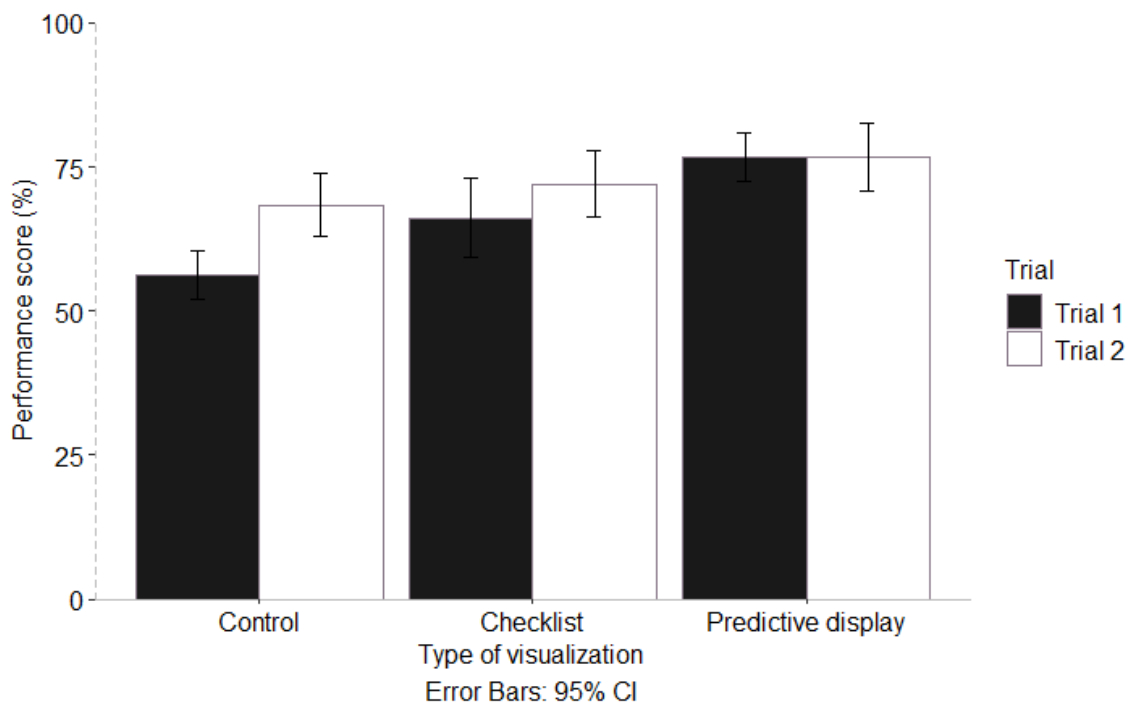


Figure 5.7. Interaction effect of trial and type of visualization for participants' performance

Table 5.13. Mean percentage and SD of performance

		Type of visualization		
		Control	Checklist	Predictive display
Trial	Trial 1	56.25 (9.12)	66.07 (15.12)	76.70 (9.38)
	Trial 2	68.40 (11.89)	72.02 (12.62)	76.70 (13.16)

*Workload (NASA TLX)*

NASA TLX tool was used to measure the workload experienced by participants. Only performance subscale was significantly different. Total workload, mental demand, temporal demand, effort and frustration were not significantly different among different levels of independent variables. Figure 5.8 illustrates the effect of trial and the type of visualization on NASA TLX subscales.

*NASA TLX Performance:* Table 5.14 illustrates the summary of the iterative modeling for the NASA TLX performance measure. In the final model, the main effect of the type of visualization was significant with  $\Delta\chi^2 = 8.38$  and  $p = 0.01$ . However, the main effect of trial ( $\Delta\chi^2 = 0.19$ ,  $p = 0.66$ ), and the interaction between trial and type of visualization ( $\Delta\chi^2 = 1.78$ ,  $p = 0.41$ ) were not significant. A model with only type of visualization as the independent variable was considered for the final data analysis. Lower values of NASA TLX performance indicate higher perceived performance. Post hoc analysis was conducted with Bonferroni correction. Perceived performance was significantly higher for participants in the checklist condition ( $b = -3.18$ ,  $SE = 1.20$ ,  $95\%CI [-6.13, -0.22]$ ,  $p = 0.03$ ) compared to participants in the control condition. Performance was marginally significantly higher for participants in the predictive display condition ( $b = -2.88$ ,  $SE =$



1.19, 95%CI [-5.80, 0.04],  $p = 0.05$ ) compared to the participants in control condition. However, no significant difference in performance was observed between participants in the checklist condition and the predictive display condition ( $b = 0.30$ ,  $SE = 1.17$ , 95%CI [-2.58, 3.18],  $p = 0.99$ ). The mean values can be found in Table 5.15.

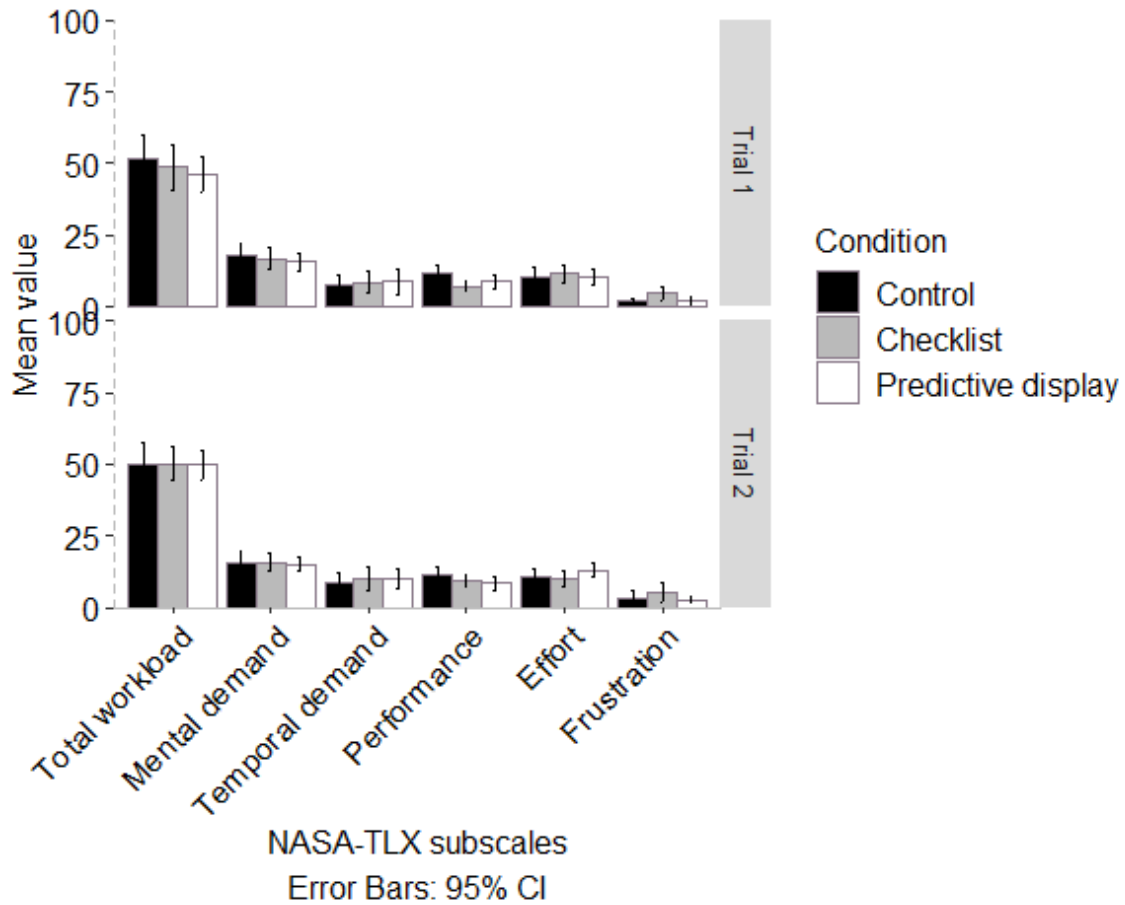


Figure 5.8. NASA TLX subscales

Table 5.14. Model summary for iterative model building for NASA TLX performance

Variable	Model1			Model2, R <sup>2</sup> = 0.001, p = 0.66			Model3, R <sup>2</sup> = 0.07, p = 0.01			Model4, R <sup>2</sup> = 0.08, p = 0.41		
	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper	B (SE)	CI Lower	CI Upper
Constant	9.34 (0.51)	8.33	10.35	9.14 (0.69)	7.77	10.51	11.21 (0.97)	9.29	13.12	11.77 (1.19)	9.43	14.10
Trial												
Trial 2				0.40 (0.93)	-1.45	2.25	0.40 (0.94)	-1.45	2.25	-0.72 (1.66)	-3.96	2.52
Experimental condition (type of visualization)												
Checklist							-3.18 (1.19)	-5.52	-0.84	-4.59 (1.67)	-7.85	-1.33
Predictive display							-2.89 (1.18)	-5.19	-0.56	-3.13 (1.65)	-6.35	0.09
Interaction between Condition and trial												
Checklist: trial 2										2.83 (2.32)	-1.70	7.36
Predictive display: trial 2										0.50 (2.29)	-3.97	4.98

Table 5.15. Mean and SD of NASA TLX performance

	Type of visualization	
Control	Checklist	Predictive display
11.41 (6.14)	8.23 (4.39)	8.53 (5.31)

## DISCUSSION

This study investigated the transfer of training effect of context based visual decision aids. More specifically, it investigated the effect of implementation of these decision aids on the SA, performance and workload of the participants. The types of visualization used included a checklist based decision aid and a predictive display based decision aid. These decision aids were designed based on the insights obtained from a previous qualitative study investigating the sensemaking process of windstorm risk engineers (Agnisarman et al., 2018). The design principles proposed by Endsley (2016) for supporting SA requirements were also considered in the design of these decision aids.

The SA of participants in the predictive display condition and checklist condition remained the same for both Trial 1 and Trial 2 for all risk inspection tasks except one: participants in the control condition achieved higher SA in the Trial 2 condition compared to the Trial 1 condition. However, their SA was still not better than that of participants in the checklist condition or the predictive display condition. This finding is promising as the participants in the checklist condition and predictive display condition were able to transfer the effect of the context-based decision aids to a similar inspection task conducted later. The participants maintained their SA in the second trial for all but one task. Their SA dropped significantly for the second task which required them to obtain fastener and weld spacing and flashing details. In the first trial, the checklist provided retrieval cues highlighting these tasks. However, in second trial, in the absence of such cues, participants failed to notice the fasteners.

In addition, the performance of the participants in the second trial was not significantly different from their Trial 1 performance. The use of the checklist helped participants by providing retrieval cues in the first study (Degani & Wiener, 1990; Reason, 1990; Wickens et al., 2015), helping them remember the steps they needed to complete in the second study as well. Additionally, the predictive display showed them what could happen to different components on the building in the event of extreme weather conditions, specifically helping them visualize what could happen in the event of a Category 4 hurricane. This knowledge helped them complete the inspection task in the follow-up study without the decision aids.

Past research investigating the effectiveness of checklist-based decision aids for training in intraoperative handover found a checklist had a positive effect on the communication of items during anesthesia handovers (Jullia et al., 2017). However, no existing research has investigated the transfer of the training effect of checklists or predictive display based decision aids. Many studies have investigated the transfer of training effect of virtual reality based training. For example, past studies investigating the transfer of training effect of virtual environments for surgery training observed that the use of virtual reality training techniques is as good or better than other conventional training methods such as video-based training (Aïm, Lonjon, Hannouche, & Nizard, 2016; Alaker, Wynn, & Arulampalam, 2016). None of these studies investigated the effect of decision aids in virtual environments for transfer of training.

As identified in this research, participants in the control condition improved their performance and SA significantly in Trial 2 compared to Trial 1. During the retrospective think aloud session post study completion, participants mentioned that the SAGAT questionnaire helped them identify what to look for. Since they were exposed to the SAGAT questionnaires in the first study, they knew the type of issues they needed to look for in Trial 2. Exposure to the SAGAT questionnaire and performance questionnaire in the first study improved their SA and performance in the second trial. A past study investigating the effectiveness of announced quizzes on exam performance identified that the group of students who took the quizzes showed higher performance on the exams (Azorlosa, 2011). This study suggested that the quizzes provided the opportunity for increased studying by the students. Additional research investigating the effect of quizzes on student performance identified similar results in addition to finding that students who were quizzed regularly had higher performance on identical, similar and new questions compared to the control condition. Quizzes appeared to increase their engagement with their study materials (Batsell, Perry, Hanley, & Hostetter, 2017). Additionally, a study investigating the transfer of training effect of head-mounted display based training for assembly tasks found that the addition of a quiz before proceeding to an actual assembly task without any assistance improved the training effect (Werrlich, Nguyen, & Notni, 2018). In our research, the SAGAT quizzes helped participants focus on issues they needed to identify, in turn improving the SA and performance of the participants in the control condition. The quizzes made them more attentive and focused on the assigned tasks. However, the SAGAT quizzes did not have any additional effect on the participants

exposed to the checklist condition or the predictive display condition. Their performance was already higher in Trial 1.

As identified in this research, no significant difference in workload was experienced by participants across study conditions or trials. This result is promising as the checklist and predictive display did not place any additional cognitive demands on participants (see Chapter 4). Higher workload can lead to lower SA (Endsley, 2016; Mahadevan, 2009). Additionally, the removal of decision aids in the second trial did not have any negative effect on participants' workload. The participants experienced the same workload in the presence and absence of context-based visual decision aids.

Though this study sheds light on the potential of using context-based visual decision aids for training windstorm risk engineers, it is not without limitations. One of the important limitations is the use of convenient sampling of civil or construction engineering students. However, their skill sets match quite well with novice risk engineers who need such training. In addition, it used simulated scenarios and simplified inspection tasks, factors that might have resulted in limited ecological validity. Additionally, the follow-up study was conducted within a week of the first one. More studies need to be conducted before we can more fully understand the transfer of training effect of these decision aids. Furthermore, as this study did not include a few trials without SAGAT simulation freezes, their effect on performance is not known.

## CONCLUSION

This study investigated the effectiveness of checklist based and predictive display based contextual decision aids for windstorm risk inspection training. Based on a mixed experimental design, the study was conducted using a virtual risk inspection scenario. Findings from this study suggest that the checklist and predictive display based decision aids were effective in supporting the SA requirements and performance of participants. Participants exposed to the experimental condition in the first trial maintained their SA and performance in a follow-up study conducted after a week without any decision aids. However, one unexpected observation was the significantly higher performance of participants in the control condition in Trial 2. When questioned about their experience, they suggested that the SAGAT questionnaire helped them focus on important tasks that needed to be completed. They mentioned that they knew what and where to inspect and what to look for. This finding suggests the potential of the SAGAT method itself for training novice windstorm risk engineers. Future research needs to be conducted with and without SAGAT freezes to identify the potential training effect of the SAGAT.

In addition to performance and SA, the participants' workload was measured using NASA TLX. The study found that the absence of decision aids in the follow-up study did not increase the cognitive load on the participants. This finding is promising because the absence of decision aids did not place any additional workload demands on participants. Though findings from this study are promising, further research is needed to investigate

the effectiveness of the training materials proposed in this study in real-world inspection tasks.



## CHAPTER SIX

### CONCLUSION

Windstorm risk loss prevention survey, the process of assessing the wind vulnerabilities of an infrastructure system to limit the extent of damages in the event of an extreme wind event, is highly subjective, depending on the skill sets of the engineers conducting the inspection. This dissertation first investigated the state of the art of an automation-assisted infrastructure inspection process and the human factors implications of such systems. While the results suggested an increased interest in the application of automation-assisted technologies to support infrastructure inspection, further investigation of the human factors aspects of these systems to better design the technology to meet the needs of the inspectors is required.

To design such automation-assisted inspection systems for infrastructure engineers, we first need to understand both their sensemaking process and their mental model of the system. To address this need the first study investigated the sensemaking process of windstorm risk engineers performing loss prevention surveys to identify their needs and the challenges they face. Using a semi-structured interview procedure, 10 windstorm risk engineers were interviewed in this study. The data obtained were then analyzed using an inductive thematic approach, and the sensemaking framework proposed by Klein et al. (2006a) was used to analyze the results of this study. This study identified several challenges faced by windstorm risk engineers, a primary one being their inability to predict the future state of the infrastructure system. Because they seldom receive feedback on the

performance of the facility after an event, it is difficult for them to predict what could happen when one occurs. This situation can be particularly challenging for novice risk engineers as they have only limited experience conducting windstorm risk inspection surveys.

The second study explored the possibility of developing context-based visual decision aids to support the SA requirements and performance of windstorm risk engineers. These decision aids, developed based on the results of previous qualitative research, included a checklist based and a predictive display based decision aid. Following a between subjects study design, 65 participants completed this study. The results found that participants exposed to the experimental conditions exhibited higher SA and performed better, with the use of context-based decision aids having a positive effect by reducing their reliance on memory. Additionally, the decision aids helped users integrate the cues available to make sense of the environment. More specifically, the checklist alone was sufficient for some tasks including the inspection of obvious issues like roof ponding, cracking and clogged drainage. However, for the tasks involving the identification of the interaction among different components in the building, predictive display provided additional benefits. For example, the tasks involving identification of various damages caused by rooftop equipment and EIFS, predictive display is more useful. These results are important to consider while designing decision aids for windstorm risk engineers.

The final study evaluated the transfer of training effect of these context based visual decision aids. These follow-up studies were conducted a week after the first study to learn

more about the SA and performance of participants in the absence of the context-based decision aids. The results of this study found that the participants in the control condition achieved higher SA and performed better in the follow-up study compared to the first study. However, the performance of participants in the checklist condition and predictive display condition remained unchanged for the most part in the second trial. During the retrospective think aloud session, participants mentioned that the SAGAT questionnaire helped them focus on the important issues, findings suggesting the possibility of using this questionnaire as a potential training mechanism for windstorm risk engineers. As the participants responded to questions similar to those in the first trial, they knew what to look for in the second, resulting in improved performance. The performance and SA of participants in the predictive display condition and checklist condition who exhibited higher performance and SA in the first trial remained unchanged in the second trial. This result is promising as the training effect of the decision aids was transferred to a similar scenario without the decision aids. However, there is a need to further investigate the training potential of the SAGAT method.

The findings from this research can be used to develop context based visual decision aids as well as training materials for windstorm risk engineers. As windstorm risk inspection is a highly qualitative process depending on the skill sets of the risk engineers, the checklist developed in this study can be used as a mechanism to standardize this inspection process. The use of a standardized checklist will streamline the inspection task and improve the quality of the inspection process. In addition, the predictive display can be used in actual windstorm risk inspection tasks to improve the Level 2 and Level 3 SA

of windstorm risk engineers. The research also uncovered several drawbacks of these decision aids. Some participants did not think that the predictive display was helpful or that it had any value beyond the training phase, suggesting not everyone perceives the benefits of predictive display equally. Moreover the use of predictive display resulted in attentional tunneling for some participants. To address these issues, in future designs predictive display can be included only to show complex interactions among different components of the infrastructure system in the event of an extreme weather condition. Additionally, the checklist used in this study was specific to the scenario used. In actual risk inspection tasks, the use of adaptive checklists can be considered. Finally, these decision aids can be used for training as well based on the transfer of training effect of these decision aids. This research also found potential for using the SAGAT questionnaire for training.

This research has the potential to provide several benefits for understanding the advantages of using context-based visualizations while performing windstorm risk inspection. Thus, it has the potential to affect the domain of windstorm risk inspection as it identified the type of information requirements of the risk engineers and developed context-based visualizations to support those requirements. The broader application of the findings from this study can influence the development of visual aids in various other sectors such as aviation, the nuclear power industry, the automotive industry, disaster response, emergency medicine and surgery. Identifying domain specific requirements is key for the development of the right type of context-based visualizations to support the specific needs of the users. Not only will the findings from this research help design visual

aids in the area of risk inspection as well as for other domains but its outcomes also add valuable knowledge to the literature in human factors.

### **Limitations and future work**

One of the primary limitations of this dissertation research is the use of convenient sampling in the second and third study. Further research needs to be conducted with professional windstorm risk engineers to confirm the effectiveness of these decision aids for actual risk inspection tasks. Further studies also need to be conducted using actual risk inspection tasks rather than the simplified simulated tasks used here. In addition, the potential of using other feedback methods such as haptic cues to minimize the bias caused by the use of automated decision aids needs to be investigated. Furthermore, there is a need to conduct additional studies to investigate the training potential of the SAGAT method. These studies could be conducted both with and without SAGAT freezes to determine their impact on performance.

### **My contributions**

During my tenure as a doctoral student at Clemson University, I was fortunate to have worked on various human factors and usability projects. I have used a number of different research approaches such as interviews, contextual inquiry, content analysis, surveys and controlled behavioral experiments to investigate human factors problems. I have conducted multiple research studies to understand the usability issues of home-based telemedicine systems. A number of journal and conference articles were published based

on the results of this research (Agnisarman et al., 2017; Agnisarman, Narasimha, Madathil, et al., 2017; Narasimha et al., 2018, 2016, 2017; Rogers et al., 2017). I have also explored how anecdotal information and publicly available performance indicators on the performance of a healthcare facility affected consumers' sensemaking as well as decision making process (Agnisarman, Ponathil, Lopes, & Chalil Madathil, 2018a; Agnisarman, Ponathil, Lopes, & Chalil Madathil, 2018b). I have also been a part of a research project investigating the effectiveness of decision aids in supporting the sensemaking process on anonymous social media (Ponathil, Agnisarman, Khasawneh, Narasimha, & Chalil Madathil, 2017). Additionally, I was a part of a research investigating the information sought by caregivers of Alzheimer's patients on online peer support groups (Scharett, Madathil, Lopes, & Rogers, 2017). Further, I have written two literature reviews: one on persuasive technologies for sustainable living and one on automation enabled infrastructure inspection systems (Agnisarman et al., 2019; Agnisarman et al., 2018).

The first qualitative study and the second controlled study of this dissertation project were published in the conference proceedings of Human Factors and Ergonomics Society's Annual Meeting (Agnisarman et al., 2018; Sruthy Agnisarman, Madathil, & Bertrand, 2019).

## APPENDICES

### Appendix A

#### Summary of Selected Articles

Article	Domain	Technology	Implementation/testing	Objectives	Key Findings
Chae et al. (2001)	Sewer condition assessment	<p>SSET: CCTV technology, optical scanner, gyroscopic technology. The system moves continuously collecting gyroscope data.</p> <p>Next step involves preprocessing of collected images</p> <p>Algorithm: Multiple Artificial Neural Network used to recognize the defects: input—preprocessed data, output—attributes of cracks such as number and dimensions</p> <p>Joint detection neural network</p> <p>Fuzzy estimation system: automated identification, classification and rating of defects based on neural network output.</p>	Prototype deployed in San Jose, CA	Crack detection of sewer line	<p>Pipe joints detected with 100% accuracy</p> <p>Overall pipe condition assessed using joint detection and crack detection algorithms</p> <p>Results not validated against conventional methods</p>
Cho et al. (2004)	Nuclear reactor vessel inspection	<p>The Korea Electric Power Robot for Visual Test (KeproVt): underwater robot, vision processor based measuring units, master control station and servo control station.</p> <p>Robot: Arranged LEDs. Used radiation hardened inspection camera and zoom lens. Also included acoustic sensor and depth sensor</p> <p>Control: Servo control station controls the robot, and master control station sends command to servo station</p> <p>Position &amp; orientation measuring unit: camera, LEDs, visual position and orientation measuring program (installed in master station). Measured based on the position of LED lights</p> <p>Automatic or manual control</p>	<p>Carried out small-scale experiments and full-scale experiments in the nuclear training center.</p> <p>Positioning and heading errors within +/- 1cm and +/-2°.</p>	Positioning of robot.	Robot inspections took 5hrs compared to 10hrs for conventional inspection

		Also developed a robot simulator imitating robot activities Algorithm:			
Jiang et al. (2005)	Underground cable system	Tracking window predict the position of LEDs. Developed an autonomous robotic platform  The control system of robot: remote host computer, data acquisition board, general control board  Viewed sensor output remotely using the interface on remote host computer  Controlled robot using the control board.  Data acquisition: dielectric, acoustic, thermal and video sensors	Compared manual and autonomous control	Underground electric cable monitoring	No difference between manual and autonomous control. Platform worked properly
Kwak et al. (2007)	Pipeline inspection	Robotic platform equipped with a sensor suite housing a sonar, CCTV camera, high-resolution imager, multi-gas logger, and 3-D laser scanner Lining: Responder collected the data. Used standard convex hulling algorithm to calculate area and perimeter Corrosion evaluation: 3-D LADAR used to obtain data on a 1.9 meter diameter and 790 meter long pipe. Photos taken at 5-meter intervals Geo-location: used a combination of different position estimation techniques (dead-reckoning technique, iterative closest point algorithm)	Three case studies: 1. To estimate cross sectional area 2. To estimate corrosion 3. To estimate pipe position	Determine transport capacity Corrosion estimation Geo-location of segments of sewer	Improved detection of material loss
Agrawal et al. (2008)	Sewer force main	Ultrasonic crawler: consists of a video inspection robot with ultrasonic transducers. Used fiber optics for video transmission and remote control. Time difference between ultrasonic signals used to calculate pipe thickness	Conducted pilot testing on a steel pipe 18 inches in diameter and 100 ft long. PitViewer software automatically analyzed the data.	Damage detection and thickness measurement of sewer line	Detected characteristics of defects such as location, severity, and depth Measured wall thickness
Reed et al. (2010)	Ship hull and harbor inspection	Remotely operated vehicle: automated and semi-automated piloting and manual control (joystick). Images taken using 3D SONAR	Did not conduct any tests	Performs ship hull and harbor detection	No information available



Had target detection module  
 Used video sensors  
 Automated control algorithm allowed operators to focus on inspection tasks.  
 ROVs can conduct complex maneuvers  
 Automatic Target Recognition (ATR) algorithms used for Real-time sensor processing tools.  
 3D reconstruction profiling from sonar data for harbor pier pilings and the running gear of the ship.  
 SeeByte – True dynamic positioning software, (ATR), 3D reconstruction, sensor driven control, advance navigation solution, world modelling and change detection algorithm.  
 2 key modules: Motion planner module & True dynamic Positioning (DP)  
 3 modes of STO – Automated , semi- automated, full manual (Joystick)  
 Geo referencing information with mosaic – situation awareness  
 Image processing technologies – thresholding and morphology to clean up sonar frames.

Ridao et al. (2010)	Dam inspection	<p>Automated Underwater Vehicle (AUV): power module — lead batteries, computer module — 2 PCs (control and image &amp; sonar processing). Operated as either AUV or ROV (tethered mode)          Acoustic modem for communication          Robot interface module: Sensors: drivers for surface buoy, Motion Reference Unit (MRU), Doppler Velocity Log (DVL), imaging sonar, echo sounder, camera, water leakage detectors, temperature and pressure sensors          Perception module: navigator and environment detector. Control module uses data from navigator and environment detector detects the position          Algorithms:          Extended Kalman Filter — navigation</p>	Carried out experiments in Pasteral Hydroelectric Dam, Spain	Crack detection of dam structure Navigation of AUV	Developed geo-referenced photomosaic of inspected walls
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wall detection and tracking algorithm

Ékes et al. (2011)	Pipe inspection	<p>Pipe penetrating radar (PPR): radar data combined with CCTV images.                  2 or more high frequency GPR antennas.                  Majority of current underground infrastructure is over 50 years old.                  GPR- emission, reflection and detection of electromagnetic waves (12.5 MHz to 4 GHz)                  Greater the change in material – more energy reflected.                  LIDAR data correlate with on board inertial navigation system (INS).                  Other sensors can be used like H2S sensor.                  Can be used along with pipe rehabilitation technology.</p>	<p>The system was deployed on a rectangular 30 inch storm-sewer pipe in Canada</p>	<p>Pipe bending symptoms and remaining service life.                  Pipe wall thickness and pipe deterioration.                  Dielectric properties of the pipe                  /affecting factors – polarization, dielectric controls, signal attenuation, background noise.</p>	<p>Demonstrated early success</p>
Murphy et al. (2011)	Post disaster bridge inspection	<p>Used three UMVs: Sea-RAI USV, VideoRay tethered ROV, YSI Ecomapper (compared these UMVs)                  Sea-RAI USV: autonomous navigation, acoustic camera, 3 video cameras. Data collected stored and displayed in a Google Earth interface.                  Controlled by a pilot                  VideoRay: acoustic camera, camera. Controlled by a pilot                  YSI Ecomapper: GPS and inertial navigation system, sonar, autonomous</p>	<p>The team inspected the Rollover Pass Bridge after Hurricane Ike</p>	<p>Bridge substructure inspection                  Debris field mapping</p>	<p>Explained findings in 3 areas:                  Control challenges: navigation and station keeping, GPS loss, obstacle avoidance                  Huma-robot interaction: members in a team need to have a shared understanding                  Multi-Robot Cooperation: having a multi-robot team will be beneficial                  Uncertain sensor data: challenges associated with handling large data set and uncertain sensor data</p>

Merz and Chapman (2011)	Infrastructure inspection (general)	<p>Autonomous helicopters  Portable ground station (provides a user interface to control the helicopter)  Flight plans provided through wireless GNC system with GPS, altitude sensors, pressure meter, LIDAR, computers  Payload with 3 digital cameras, thermal camera.</p> <p>Dynamic Airspace Controller (ADAC)  Plant Phonemics- Spectral reflection of plants to compare growth</p>	<p>The helicopter was successfully deployed in the field. First person view (FPV) with video goggles.  Beyond Visual range (BVR)  Automated helicopter with Cots 2 D LIDAR  Autonomous (GNC) guidance, navigation and control  LIDAR 270° scan range  Hardware in loop (HIL) simulation in real time.</p>	<p>Height estimation by LIDAR &amp; Extended Kalman filters for Helicopter state.  2 Flight modes:  Pirouette descent and Waggle cruise  Separation detection between other aircrafts controlled by Automatic</p>	<p>System was able to collect data and capture images that had sufficient details for analysis</p>
Chen et al. (2011)	Highway bridge monitoring	<p>Aerial photography: Digital color photography.  Camera set up inside a Cessna C210L plane. A pilot and camera operator in the plane.  SI-SFAP: commercial remote sensing (CRS) technique  Used a bridge surface condition index (BSCI) to rate the condition of bridges from the photographs taken  Rectified and georeferenced the images  GPS for tracking and navigation</p>	<p>Data collected during construction of the Cuthbertson Road Bridge, NC</p>	<p>Detect bridge deck distress  New construction monitoring</p>	<p>Remote sensing technology can detect defects on bridge deck</p>
Lee et al. (2012)	Underwater application	<p>Underwater robot: 2 pressure vessels (computer control system and sensor processing units)  4 horizontal and 2 vertical thrusters  Two cameras with 2 LED lights  Sonar  High resolution HAD CCD sensor  Main control computer, optical and sonar processing computer and acoustic signal processing computer communicate through high speed internal network  Algorithms:  Used a color restoration algorithm  Template matching algorithm (target object detection)</p>	<p>Carried out indoor experiments  Video collected by the camera used to test the detection and image restoration algorithm  Object used: cross, cone, sphere, cylinder (in air and water)  Experiment 1: used pictures taken in underwater environment  Experiment 2: Used images of objects taken</p>	<p>Vision based autonomous navigation  Underwater color restoration</p>	<p>Best result for experiment 1. Lower performance observed for experiments 2 and 3. However, slightly better results for experiment 3 because of the algorithm  Use of color restoration algorithm improved the performance of</p>

		Mean shifting algorithm (object tracking)	in air (without color restoration algorithm) Experiment 3: Used images taken in air (with color restoration algorithm)		underwater object tracking
Eschman et al. (2012)	Building inspection and monitoring	Octocopter: Gyroscope, accelerometer, barometric altitude sensor, GPS & 3D magnetic sensor (for navigation), camera Camera automatically took pictures Manual flight control	Took 12,000 images of a building	Damage inspection and crack detection of building	The images provided valuable information
Larrauri et al. (2013)	Powerline inspection	Algorithms: Image processing: Pattern recognition techniques Crack detection algorithm Edge detection algorithm Proposed a system to investigate power lines: RELIFO UAV flies as close as 10 ms over power lines Ground station: antenna, 3 computers, (flight plan, telemetry, UAV-ground station communication managed by first computer, second computer receives video from HD camera and telemetry, third computer receives images from IR thermal camera, also sends online reports via SMS and email)	Two field application: 1. to calculate the distance between vegetation, trees and buildings to the power line based on HD camera images—generates an alarm based on the distance (go off for distances less than 5m) 2. to detect hotspot based on IR thermal images: automatically sends report (SMS, Email) about hotspots	To inspect power lines for possible issues	Measured distances and detected hotspots.
Torok et al. (2013)	Concrete crack detection	Robot based image collection system. 3D maps for (USAR) – structural light and visual. (SLAM) simultaneous localization and mapping Uses Structures from motion (SfM) for image processing	Autonomous concrete crack detection in post-disastrous buildings.	Image-based 3-D reconstructions Used a 3-D crack detection	Robot-based image collection method is ideal for collecting images, especially after a disaster.

		<p>(SfM) uses around 50 images to use for (SIFTGPU) scale invariant feature transform graphics processing unit for feature point detection.</p> <p>Output from (SIFTGPU) placed into clustering Multiview algorithm to generate 3D point cloud model.</p> <p>Poisson surface reconstruction approach for color mash.</p> <p>Algorithms: Crack detection algorithm Aerial direction algorithm with orthonormal axes.</p>		Develops continuous surface model.	
Painumgal et al. (2013)	Underwater pipeline (lab experiment)	<p>PICTAN Autonomous Underwater Vehicle (AUV): Equipped with green cone laser, fisheye lens camera and LED lights</p> <p>Images captured and stored in SD card. Later analyzed to assess the pipe condition</p> <p>Microcontrollers processes the image and controls the autonomous position of vehicle</p> <p>Algorithm: Real-time position estimation algorithm and offline position estimation algorithm</p>	<p>Algorithm was tested using images collected under dry lab condition by placing vehicle in a 760mm dia, 1.5 meter long pipe</p> <p>Subsequent lab tests in pipeline filled with water and pipeline with flowing water</p>	Position estimation of robot	Validated real-time position estimation technology
La et al. (2013)	Bridge deck inspection	<p>Holonomic mobile robot equipped with navigation, motion planning sensors (2 GPS units and one IMU sensor) and NDE sensors (laser scanners, GPR units, seismic/acoustic array sensors, electrical resistivity probes, digital cameras, panoramic camera)</p> <p>Control: 3 industrial standard computers with one running Robot Operating System (for navigation) and other two running Windows OS (NDE sensors). These computers are connected to each other using Ethernet and connected with remote computers using WiFi</p> <p>The data collected visualized and analyzed using remote computers</p> <p>Robot stops and collects data using NDE sensors</p>	<p>Navigation system tested on campus</p> <p>NDE sensors validated through field deployment in NJ, USA</p>	Deck inspection and evaluation Robot localization and navigation	Better localization and navigation with EKF- based navigation 3-4 times better performance compared to conventional NDE testing

		<p>Controller used a GUI to control the robot, sensors and for visualization</p> <p>Algorithms: Used control algorithm (coordinate between sensors and navigation) Extended Kalman Filter (EKF) based navigation</p>			
Ellenberg et al. (2014)	Masonry crack detection	UAV with high resolution camera. Crack detection using edge detection and percolation approaches	<p>Conducted preliminary tests to determine how crack size detection affected by distance (on paper and actual masonry wall)</p> <p>Third study conducted using a manned helicopter to collect RGB and IR images</p> <p>However, did not conduct tests with UAV. Results reported based on the helicopter test.</p>	Masonry crack identification	Challenge: environmental conditions, flight control, noise in the data
Ellenberg et al. (2014)	Bridge	<p>UAV and remote sensing: UAV, powered by a battery equipped with 2 cameras, Altitude and navigation: ultrasonic sensors, gyroscope, accelerometer, magnetometer, pressure sensor</p> <p>Kinect: IR laser projector</p> <p>Image processing algorithms</p> <p>UAV took pictures of the structure</p> <p>UAV controlled by any Wi-Fi device</p> <p>Algorithm to identify markers (measurement algorithm)</p>	<p>Crack detection: Tests conducted in lab. Camera moved over a paper with lines of different thicknesses. Carried out tests on a masonry wall using built-in UAV camera</p> <p>Deformation: Lab steel deck mockup</p> <p>Field demonstration: Flew UAV over a pedestrian bridge</p>	Bridge crack detection and deformation measurement	Algorithm identified markers
Halfawy and Hengme	Sewer system	<p>CCTV video</p> <p>Multiclass support vector machine</p> <p>Algorithms for fault detection, debris detection etc...</p>	Prototype tested in Regina and Calgary, Canada, to validate the algorithms	Camera motion analysis algorithm	Results compared with the actual inspection report using CCTV. Results

echai (2014)				Automated identification of ROI algorithm Automated debris detection algorithm Automated joint displacement defect detection algorithm Frame classification algorithm Frames segmentation algorithm	were in agreement with the operators' observations
Son et al. (2014)	Bridge inspection	<p>Robotic system with camera mounted to take photographs of bridge structure Robotic system captured color images</p> <p>Models: Rust classification model: Classifiers used: support vector machine (SVM), back-propagation neural network (BPNN), decision tree (J48), naive Bayes (NB), logistic regression (LR), and k-nearest neighbors (KNN) Blasting decision made by calculating the percentage of rust in the figure</p>	<p>Tested algorithms using the images taken in a simulated condition when a robot takes images of bridge using a mounted camera Took 40 images: 22 rust images &amp; background images</p>	Corrosion detection and blasting area detection of bridge structure	<p>97.95% average accuracy of rust classification 97.48% blast area detection accuracy 0.57s/ image process time</p>
Lim et al. (2014)	Bridge deck maintenance	<p>ROCIM system has a mobile robot, canon camera, laser sensor and one laptop. Images were collected and analyzed using Laplacian of Gaussian (LoG) algorithm. Differential GPS, Inertial Measurement Unit (IMU) are not in ROCIM robot, but recommended by the researcher. Advanced nondestructive evaluation (NDE) sensors can be used for calculating depth and severity of the cracks. To generate navigation map ROCIM uses simultaneous localization and mapping (SLAM) algorithm. Algorithm to generate efficient rectilinear</p>	Performed indoor and outdoor simulations and experiments	Bridge deck automated crack inspection	<p>Collected images and created crack maps Crack detection algorithm works for real cracks</p>

		<p>coverage paths developed by Muzaffer.  Mapper3 software  Orientation and location of the robot based on Monte Carlo localization (MCL) algorithm  Laplacian of Gaussian (LoG) algorithm used for image processing to crack detection.  Compared RIP (Robotic inspection plan) GA and RPI Greedy algorithms for path finding. GA performs better than Greedy.  Future work to use impact Echo and Ultrasound surface wave (NDE Sensors) for depth (3d) evaluation.</p>			
Steele et al. (2014)	Oil and gas refinery inspection	<p>The robot  Sensors: navigation sensors (GPS receiver, digital compass, scanning laser range finder, IR proximity sensor and navigation cameras), inspection sensors (microphone, methane gas sensor, thermal imaging camera, network video camera)  Command, control and communication system: Wi-Fi communication link  Tele-operation mode, autonomous operation mode and shared control mode  GPS used for navigation  Kalman Filter  Robot supervisory control system  Navigation Algorithm  RMP enabled motion controllers</p>	Carried out preliminary tests in their mechanical room	Inspection of oil and gas refinery Navigation of robot	Observed that controlling a robot only using streamed video was challenging
Villarino et al. (2014)	Road infrastructure	<p>Photogrammetric method: Calibrated photographic camera, used 2D and 3D modeling  Laser scanning method: Static laser scanning system, mobile scanning system with LIDAR and navigation system  Mobile inspection unit: laser scanning system (2 LIDARS), navigation system, thermographic camera, multi-camera computer viewing system, GPR, laser profilometer  System integrating all these sensors</p>	Conducted tests in Spain	Inspection of road infrastructure Data management	Geomatic methods can be successfully used for infrastructure inspection



Gucunski et al. (2015)	Bridge deck inspection	<p>Vehicle generated the 3D model of the area</p> <p>Software for visualization and data management</p> <p>Robot (RABIT) using multiple non-destructive evaluation.</p> <p>Robotic system with fully developed sensors. The main focuses were rebar corrosion, delamination and concrete degradation. The system houses 4 technologies: electrical resistivity (ER), impact echo (IE), ground-penetrating radar (GPR), ultrasonic surface waves (USW), 2 cameras, 2 GPS antennas to navigate. In addition, a base GPS station at the beginning or end of the bridge. Autonomous operation facilitated by path planning algorithm. Three-fold production rates compared to a team of 5 NDT technicians.</p> <p>Developed a tool that identifies crack, spalls and patches.</p> <p>Algorithm: Path planning algorithm</p>	Field deployed and collected data using NDE sensors	Primary objective was bridge inspection Developed a data visualization technique	Efficient process with less traffic interruption
Khan et al. (2015)	Bridge deck inspection	<p>Unmanned Aerial Vehicle (UAV) based inspection: UAV with GoPro camera for image collection, FLIR TAU2 IR camera for thermal imaging</p> <p>Airborne bridge inspection: using helicopter with IR camera, RGB camera,</p> <p>Inspection using ground transportation: Video RGB camera, IR scanner mounted on a vehicle</p>	An actual field was inspected using UAV, helicopter, ground transportation and portable cart	To detect bridge anomalies (surface cracking and internal delamination)	Obtained similar results for both UAV-based and portable cart based inspection Limitation of airborne inspection (maintaining a distance) mitigated through UAV
Wang and Birken (2015)	Surface and subsurface assessment of roadways	<p>The Versatile Onboard Traffic Embedded Roaming Sensors (VOTERS): multi-sensor mobile data collection van: completely automated data acquisition system</p> <p>Consists of acoustic, optical, electromagnetic and GPS sensors. Texture depth calculated using acoustic data captured by microphone. Pressure sensor calculated the roughness index. Camera images used to observe cracks. Millimeter-wave radar detected the roughness and quality. Data then processed and geo-centered.</p>	Real world implementation in Boston, MA. Six 5-hour field tests conducted	Crack detection of roadways Other condition ratings	Findings were compared against professionally done condition survey 85% correlation for 400 road segments Condition ratings are non-subjective

Ekens (2016)	Underground pipe infrastructure	<p>CCTV, LIDAR- and SONAR-based. System is deployed on a remotely operated vehicle (ROV)</p> <p>Uses visual and quantitative technologies</p> <p>CCTV data will be correlated with GPR data</p> <p>LIDAR: quantitative measurement of insides of pipes</p> <p>The ROV had 3 cameras &amp; is a float-based system</p> <p>Performs accurate cross-sectional analysis and sediment volume</p> <p>Name – (VUEmspi) multisensory pipe inspection</p> <p>Laser profiling for pipe parameters</p> <p>CIPP (cured in place pipe) engineering will benefit from VUEmspi.</p> <p>Onboard inertial navigation system</p> <p>Planer laser performs continuous pipe ring profiling</p> <p>Pilot test locations were Abbotsford, B.C., and Boulogne, France.</p>	Deployed in France	Quantify sediment distribution in underground pipe infrastructure	<p>LIDAR estimated the size and shape of the pipe</p> <p>SONAR profiled the pipe and estimated sediment and debris volume</p> <p>The findings helped managers in prioritizing the areas need to be cleaned</p>
Liu et al. (2016)	Curtain wall	<p>Multiple technologies:</p> <p>Developed a Building Information Model (BIM), point cloud model (using LIDAR technology)</p> <p>Data collected on site using UAS equipped with a camera taking pictures every 5 seconds</p> <p>Used GPS technology to locate the location of photo taken by the UAV</p>	<p>Inspected a 12-story building curtain wall</p> <p>Laser point cloud compared against photogrammetry point cloud</p>	Built models	<p>UAS was found to be effective and had many advantages</p> <p>LIDAR points concentrated more linearly on the exterior surface of the curtain wall and distribution was more even.</p>
Ellenberg et al. (2016)	Bridge inspection	<p>UAV: Flight control using pressure sensor and GPS feedback.</p> <p>GoPro camera sends live video to a GoPro app on smartphone</p> <p>Photos captured using Sony NEX 7 camera to compare with UAV imagery</p>	<p>Lab scale study (turned off GPS)</p> <p>Deflection: Images taken without and with load on the steel grid deck</p>	<p>Bearing deformation</p> <p>Deflection measurement</p> <p>Corrosion assessment</p> <p>Crack identification of bridge structure</p>	<p>The deflection measures using GoPro camera were not very accurate</p> <p>UAV manual corrosion measurements were</p>

		<p>Images processed using camera calibration and homography          Algorithms: Camera calibration algorithm          Homography: images flattened to plane          Crack detection algorithm          K-means algorithm</p>	<p>Corrosion: Images taped to the steel grid. Then images of grid taken          Crack: images taken of existing crack on masonry wall using GoPro. Then used image processing techniques.          Conducted inspection on satisfactory condition bridge, fair condition bridge, poor condition bridge and supplementary bridges</p>		<p>more accurate than k-means method          Cracks identified correctly</p>
Harris et al. (2016)	Bridges	<p>Commercially available remote sensing technologies.          Used multiple remote sensing technologies          Collected basic optical imagery.          Close range photogrammetry using camera          Surface imagery using StreetView-style photography/Bridge Viewer Remote Camera System (BVRCS), GigaPan          LIDAR          IR thermography          RADAR          Algorithm:          3DOBS algorithm (close range photogrammetry)</p>		<p>International Roughness Index (IRI)          Spall detection of bridge structure</p>	<p>Provides a basis for more in-depth observations/inspections          Better performance for photogrammetry compared to LIDAR</p>
Lins and Givigi (2016)	Structural health monitoring Lab study (bridge)	<p>Fully automated SHM. Autonomous robot system with camera and GPS          Trajectory control algorithm to control the trajectory          Self-navigation, detection and measurement of defects: laser and ultrasonic sensors          Robot operating system (ROS) used for remote communication.          Visual Path tracking for navigation          ROS master and nodes – Navigate, defect detection, measurement and data storage.          Command velocity nodes controls robot motors.          SQL, ODBC interface for database management.          Clearpath husky robot with 24 Optitrack camera          Algorithms: Control algorithm, vision-based measurement algorithm (relative pose of target), crack detection algorithm, crack measurement algorithm</p>	<p>Lab study using camera instead of GPS          Camera images are fed to vision-based measurement algorithm          Crack detection algorithm and crack measurement algorithm.          After object detection image imputed in crack detection algorithm.          Image processing – crack measurement algorithm.</p>	<p>Computerized maintenance management system to support decision making.          Navigation          Crack detection</p>	<p>The system navigated successfully, and it detected and measured defects without human involvement.</p>

Henricks on et al. (2016)	Multiple application s: railroad, pipelines, bridges, roads	Unmanned aircraft system (UAS) with sensors and ground equipment. The sensors selected: CMOS sensors for visual and IR images, Canon DSLR camera for RGB imagery with external GPS antennae, and a GoPro silver edition for situation awareness. Used both fixed wing and rotorcraft flights Ground equipment: ground control station notebook computer, telemetry radio, R/C transmitter, flight batteries, tools such as screwdriver and plier	Conducted studies to inspect if vegetation encroached on runway infrastructure. Vegetation areas and non-vegetation areas differentiated using different colors.	Develop a mechanism to quickly explore infrastructure	The system was able to collect sufficient data to perform infrastructure assessment.
Özaslan et al. (2016)	Dam penstock inspection	Micro Aerial Vehicles (MAVs): Intel i7 board, 2 LIDARs, four cameras, IMU and power LEDs Data from pose estimation camera, map, IMU data and LIDAR data fed to the Robot Operating System One camera tracked the features of the dam to update its path. Researchers also explained how they analyzed these data and the equations they used Operators provided commands using RC interface Algorithm: Iterative Closest Point (ICP)	Inspected penstocks of Carters Dam, GA	Pose estimation and automated inspection of dam penstock	Achieved complete autonomy in inspection 360° panoramic images and 3D textured reconstruction.
Yoder and Scherer (2016)	Train bridge	MAV: Intel i7 dual core processor, LIDAR, cameras, barometric pressure sensor, IMU Effective 3D path planning algorithm Surface Frontier: #D surface exploration and incremental path planning algorithm. Frontier exploration algorithm MOV exploring river uses frontier shoreline algorithm. SPARTAN path planner Depth enhanced visual odometry Kalman filter to fuse IMU, visual odometry, pressure and GPS Developed algorithm for autonomous navigation	Field deployment	Infrastructure exploration and infrastructure modelling. Arbitrary geometry rapidly modelled outdoor structure 3D bounding box around the structure to scan all the surfaces.	Autonomous exploration is compared with manual control Autonomous system performed as good as a skilled pilot. Entropy reduction method to determine best exploration path.

Ellenberg et al. (2016)	Highway bridges (indoor and lab studies)	<p>DJI Phantom with GoPro camera  Images extracted and applied crack detection algorithm  Outdoor: GoPro and 2 IR cameras  Videos streamed to the ground to the pilot  Conducted a helicopter flight test to obtain a global view</p> <p>Algorithms:  K-means</p>	<p>Conducted laboratory study  Images collected using the camera were extracted and detected using the crack detection algorithm  Region of images without crack was removed using K-means algorithm  Corrosion identification based on difference in color  Bearing and beam deformation measurements calculated from the images  Outdoor testing with GoPro and IR cameras</p>	<p>Image processing  Crack identification algorithm  Corrosion identification of highway bridge</p>	<p>Actual and UAV-based measurements were comparable</p>
Protopapadakis et al. (2016)	Tunnel inspection	<p>The robotic platform: robotic arm, visual cameras  Mobile wheeled vehicle with robotic sensors  Robotic arm takes the measurements  Cameras and laser sensors  State of the art algorithm is used to detect the defects  Faro 3D Laser scanner measures and calculates deformation in lining.  11-ft crane with robotic manipulator  Six Degree of Freedom for robotic arm to cover all directions.  Recognition algorithm and #D information extraction algorithm.  Crack detection done by deep learning approach  Visual inspection is based on convolutional neural network—carried out by multi-layer perceptron method.</p>	<p>System was evaluated in road and railway tunnel on Egnatia Highway, Greece, and London underground infrastructure</p>	<p>Integrated Global Controller (ICG) to identify position of crack, semantic info of tunnel structure.  Defects in concrete using monocular camera RGB image.</p>	<p>Crack detection in tunnel inspection</p>

Dong et al. (2016)	Nuclear power plant water-filled infrastructure Field experiment in nuclear simulation pool	<p>Update reconstructed lining (based on previous plan) with new images.  Photogrammetric methods are used for 3D crack.  Remotely Operated Vehicle (ROV)  Underwater robot: contains control cabinet, buoyancy module, propellers, cameras, manipulator, depth gauge, SONAR, accelerometer, gyroscope, magnetometer. Visual inspection made possible through IST-REES irradiation resistant camera.  Control box: has a personal computer, liquid crystal display monitor, 2 joysticks, peripheral buttons  Operator communicates with the underwater robot based on the information from the sensor data  ROV can be controlled through user interface, through peripheral buttons and joysticks, and through handheld controllers.  Control system: control board receiving commands from the controller transfers the signal to the propeller to execute the command.</p>	Conducted field test in reactor simulation pool Conducted a simulation study Conducted radiation testing	Depth control Navigation and location of ROV in nuclear power plant	The performance was good Validated algorithms
Fujita et al. (2017)	Asphalt pavement crack detection	<p>Mobile mapping system (MMS): consists of a vehicle with GPS, laser scanners, cameras and other equipment. Convolutional neural network—visual inspection  Pixel level classification – using support vector network  Gaussian function varying scales are used for multi-scale convolution  F measure was used to evaluate crack detection accuracy  F measure is the harmonic mean between precision and recall  Hilditch’s algorithm was used to detect centerlines of the cracks  Morphological transformation  Image processing based on subtraction using smoothed images by the</p>	Collected 100 road surface images using mobile mapping system Conducted tests to evaluate the new method.	Crack detection of asphalt pavement	Proposed machine learning algorithm for image processing was compared with the conventional technique Proposed method improved the crack detection accuracy

		<p>median filter and multi-scale line filter based on Hessian matrix.</p> <p>Crack detection processing steps—probabilistic relaxation based method and a locally dynamic thresholding method.</p>			
Yeum et al. (2017)	Road pavement inspection	<p>Vision sensors on serial inspection platforms. The camera is completely automated</p> <p>Developed a new technique (RILVI) to extract Region of Interest (ROI) from the collected images.</p> <p>Fiducial markers were used in TRI (targeted region of interest) coordinate systems.</p> <p>iWitness-Photogrammetry software, PhotoModeler-close-range photogrammetry and image-based modeling were used for automatic matching</p> <p>Horn’s method used for 3D coordinate transformation.</p>	Lab test on full-scale highway design structure	Performs visual inspection of civil infrastructure.	Validated the new method
Eschman and Wundsam (2017)	Bridge inspection	<p>UAS equipped with airborne NDT devices such as visual camera, LIDAR and Long Wavelength Infrared (LWIR)</p> <p>3D model building completed using the images collected using the images collected highlighting the intensity of damages</p> <p>LWIR sensor data used to measure humidity and LIDAR data used for surface recognition and deformation detection</p> <p>Algorithms: Automated crack detection algorithm</p>	No study explained	Crack detection of bridge structures and dashboard development	<p>Developed a web-based GIS platform equipped with visualization tools and databases</p> <p>It allows the visualization of the data collected using sensors</p> <p>This platform can be used via a user interface providing information including name of structure, construction details and thumbnails.</p>

Javadnejad et al. (2017)	Pipeline inspection	<p>Data collected using UAS with the help of a Nokia RGB camera and LIDAR sensor. The images were processed using Structure from Motion (SfM) technique. The accuracy of this method was compared using the ground control points (GCP) and check points (CP) established in the ground.</p> <p>These ground target points were traversed using radial traversing Total Station method. The SfM and LIDAR point clouds were georeferenced. Civil Integrated Management (CIM) model was developed by creating a geometric 3D model. Algorithm: Random sample consensus algorithm</p>	Data collected from a storage yard to store gravel, asphalt grindings, debris, spare bridge parts, and piping material in Oregon. SfM model based on UAS images was compared against LIDAR point clouds.	Pipe feature extraction	<p>Developed a 3D model based on UAS aerial imagery. Generated detailed point clouds for pipe feature extraction. Pipe feature extracted using SfM models were less consistent compared to LIDAR model. However, UAS based method was less time consuming and more convenient than LIDAR method.</p>
Moradi and Zayed (2017)	Sewer pipeline inspection	<p>Data collected using CCTV Real-time supervised anomaly detection was performed using Hidden Markov Model (HMM) The proposed method facilitated real-time automated anomaly detection</p> <p>Data was split into training and testing set</p> <p>Algorithm: HMM with Viterbi algorithm</p>	Data was collected using CCTV camera from City of Laval, Quebec, Canada	Sewer line defect detection	<p>Results revealed that the proposed method is capable for detecting anomalies</p> <p>Reported accuracy = 82.5%</p>
Moselhi et al. (2017)	Bridge inspection	<p>Explored data fusion technology for bridge inspection.</p> <p>Data collected using GPR and IR technique were fused to generate new and improved images. IR images were thermal processed and GPR 2D scan data were converted to 3D images. These two were then transformed to the same coordinate system. The new fused images were used for feature extraction.</p> <p>Algorithm: Wavelet transformation</p> <p>Image processing technique: histogram equalization, threshold, edge detection, background subtraction and image segmentation</p>	<p>A concrete bridge located in Laval, Canada was inspected using this technology</p> <p>Results were compared against IR only, GPR only and conventional hammer sound and visual inspection techniques. The fusion technique's result were more accurate and close to visual inspection technique</p>	Bridge defect detection	<p>The new method produced more accurate result close to actual condition. Image processing prior to image fusion improved accuracy.</p>



Vong et al. (2017)	Railway culvert and tunnel inspection	<p>Used small scale UAS equipped with LIDAR technology to measure cross sectional shape of the culvert. This method also helped the UAS to align autonomously with the centroid of the cross section.</p> <p>The UAS transmitted collected data to the ground station computer (GSC)</p> <p>Flight controller can switch from autonomous to semi-autonomous mode by using data collected using the LIDAR technology</p> <p>Localized centroid using LIDAR data</p> <p>Navigation: Using commercially available flight controller. A proportional-integral-derivative (PID) controller was used in semi-autonomous mode.</p> <p>Algorithm: Centroid aligning algorithm</p>	Experiment was conducted in a small tunnel built to simulate field condition.	To achieve self-stabilization in a confined environment	The algorithm was found to be reasonably robust
Wang et al. (2017)	Catenary bridge inspection	<p>A camera system mounted on a car for inspecting every component of a catenary.</p> <p>Camera system consisted of up to 25 area cameras with varied field of views.</p> <p>A post detection module to trigger a signal at a specific distance relative to catenary posts. Laser sensors mounted upward were used for reliable detection.</p> <p>Cameras were controlled using a GUI. Images taken using the cameras can be viewed on the interface.</p> <p>Proposed an intelligent analysis system to automatically detect defects based on localized structural analysis followed by the use of detection algorithm.</p>	This system was used to inspect several catenaries.	Defect detection	Achieved reproducibility implying accurate post detection and trigger signal generation.
Hiasa et al. (2018)	Bridge inspection	<p>Data collected using commercially available drone equipped with camera, and IR thermography (IRT) sensors.</p> <p>A combination of these two technologies were used.</p>	<p>Images of a bridge were taken in Florida. Cracks were simulated on paper.</p> <p>In the second experiment, thermal images of 10 x 10 cm</p>	Crack detection	<p>0.1mm thick cracks were observed from enlarged images taken from 1-3m distance.</p> <p>IR camera has the potential of using in</p>

			lattice pattern squares on a brick wall were taken using IR camera mounted on a drone.		drone based structural monitoring
Hackl et al. (2017)	Bridge inspection	Utilized UAV photogrammetry to obtain topographical information. A pilot and camera operator controlled the UAV. A commercially available UAV platform, DJI inspire 1 quadcopter was used. Terrestrial images were taken using a Canon DSLR camera. Images were georeferenced. Image preprocessing, camera calibration, sparse point-cloud reconstruction, dense point-cloud reconstruction, mesh reconstruction, mesh refinement, mesh texturing, and accuracy assessment techniques were used to develop 3D model from 2D images. This 3D mesh was used to generate computations model to run fluid dynamic simulation during bridge risk inspection to understand its hydraulic stability. OpenCV, openMVG and openMVS software platforms were used. The complex flow field around the bridge was analyzed using OpenFOAM.	A bridge located in the submountainous region of Switzerland was inspected using the method explained.	Runoff flow determination and its impact on a structure's hydraulic stability	Complex flow situations were simulated using 225 topographical images collected using UAV
Lins et al. (2018)	General application	An Internet Protocol(IP) camera mounted on an autonomous robotic system. The processing unit in the robot processed the image data collected using various algorithms. Algorithms: vision-based measurement algorithm (VBM), velocity estimation algorithm (VE), crack detection (CD) and crack measurement (CM) algorithms. The algorithms ran in real-time and provided the engineers with output. Operated in fully autonomous mode or with human intervention. Data transferred to a remote station via Wi-Fi or radio modem.	Carried out a test in an indoor environment replacing GPS with camera. Carried out 5 trials using the same robot under the same environmental condition.	Crack detection and measurement	Robot followed a trajectory without much variance in terms of distance and time across multiple trials. Images were processed as it navigated through the trajectory.

		Used ROS comprising of ROS master and nodes controlling specific tasks			
Dabove et al. (2018)	Post catastrophic inspection of a cultural heritage	Data collected 20m far from the church using 2 commercially available tablets Acquired positions using GPS Some images gathered using Canon EOS 5D Mark II camera Topographic survey completed using total station. Model generated from collected data using PhotoScan software. 3D point cloud and texturized 3D models were created. Algorithms: Nearest neighbor algorithm for cloud to cloud distance comparison	Data collected from Sant'Agostino Church in Amatrice after the earthquake of the August 24, 2016. Point clouds generated using images collected through tablets were compared against that created using images from camera.	Post-earthquake inspection	The difference between tablet and camera 3D models is less than 2 cm. Tablets can be potentially used in emergency situation to save time.
Rea and Ottaviano (2018)	General industrial sites, structures and infrastructure inspection	THROO (Tracking Hybrid Rover for Overpassing Obstacles) robot was used to equip inspection equipment. Three levels of autonomy: complete teleoperation, safeguarded teleoperation and autonomous navigation Data transmitted over analog video transmitter or radio modem in teleoperation. Waypoint technique is used in autonomous mode. T0.his paper utilized complete teleoperation mode. The sensors used for inspection and monitoring tasks are; infrared camera, an electronic board equipped with accelerometer, gravity and gyroscope sensors, GPS sensor, magnetic field and acceleration sensors, gravity and gyroscope sensors, GPS sensor, magnetic field and acceleration sensors, navigation camera, infrared sensor, Xbox Kinect, and 2 micro cameras. Data displayed on a tablet and laptops. Used tablet for navigation control. A controller controlled the interoperability of sensors.	The technology was tested in an indoor laboratory environment. An electrical component was tested.	Defect detection	Integration of sensor data provides inspectors an opportunity to inspect 3D and thermal images of objects or structures.

Algorithms: Control algorithm

Khaloo et al. (2018)	Bridge inspection	<p>A six-rotor hexacopter equipped with a camera was used for data collection. Further, a GoPro camera was also used.</p> <p>Each part was covered by multiple images arranged in overlapping strips.</p> <p>UAV ground control station planned the flight paths.</p> <p>An observer provided guidance to the UAV control pilot via remote control radio link.</p> <p>Images converted to 3D point clouds using SfM method.</p> <p>Algorithms: Scale-Invariant Feature Transform (SIFT), Binary Robust Invariant Scale Point (BRISK), Speeded Up Robust Features (SURF) for feature extraction.</p> <p>Fast Approximate Nearest Neighbors (FANN) for feature matching across image pairs.</p> <p>Semi-Global matching (SGM) algorithm for transforming sparse 3D point cloud to dense point cloud.</p>	<p>Placer river bridge in Alaska was inspected using this method.</p> <p>UAV based point cloud was compared against point cloud generated using shift-based LIDAR.</p> <p>Point clouds generated using UAV captured images compared against a combined model created from both UAV and human inspector captured data.</p>	Defect detection	<p>Image based point clouds exhibited increased noise level compared to LIDAR point clouds.</p> <p>UAV point clouds and combined model had similar noise levels.</p> <p>However, UAV based point clouds were better than LIDAR point cloud in terms of completeness and resolution.</p>
Attard et al. (2018)	Large Hadron Collider (LHC) tunnel inspection	<p>Data collected using a Train Inspection Monorail (TIM). Sensors mounted on a robotic arm extending from one of the wagons.</p> <p>Images collected using a Nikon 1 V3 Mirrorless camera automatically and saved to a repository.</p> <p>Navigation made possible through an encoder measuring the distance travelled, fitted to the traction wheel. Cumulative errors avoided by position bar codes installed next to monorail every 100m.</p> <p>Proposed a computer vision technique, Tinspect Pre-processing – downsampling and enhancement.</p>	<p>Tested the image processing technique proposed on images taken from LHC tunnel.</p> <p>In this experiment, camera was mounted not on a robotic arm, but on a tripod.</p>	Defect detection	<p>Observed an overall accuracy of 81.4%.</p> <p>System detected changes as small as 10cm. Provided only a limited view of tunnel since a single wide angle lens was used.</p>

Prior to image comparison, image registration completed to align images to the same coordinate system.

Algorithms: Mosaic algorithm using binary detection for feature extraction, Canny edge detection algorithm, correlation matching.

Change detection techniques used to identify difference between query images and survey images. Pixel-based and object-based change detection methods adopted.

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## Appendix B

### Interview Questions

#### Demographic & Background

1. Age
2. What is your educational training and certification?
3. What is your work background and current position?
4. What was your designation when you joined this company?
5. How long have you been working as a field engineer?
6. Have you been doing the same thing for all these years?
7. Did you do any other jobs before this?
8. How long have you been working for AIG?
9. How many surveys do you perform a year? How many total surveys had you performed?
10. Do you have any post-catastrophic inspection experience?

#### Field inspection

11. Could you please explain to me what you look for when you go for an inspection?
12. What initial hypotheses do you develop based on the wind speed?
13. Could you describe a recent inspection that you performed?
14. What are the mental processes involved?
15. How do you estimate the damage based on what you see in this picture?
16. Could you please describe each sub-step involved in this step?
17. What judgement did you/do you make in this step?
18. What are the assumptions that you make here?
19. How did you infer something based on the available information?
20. Do you think that you had to use your cognitive skills to carry out this step successfully (eg: judgement, assessment, problem-solving, decision making, inference etc...)? How did you use them? Which skill do you think is important?
21. What mistakes/errors might a less-experienced person make at this step?  
Go to powerpoint (slide 2)
22. What would you do when you do not have sufficient information to confirm a hypothesis? For example, if there is no manufacture information available, how will you conclude if that window/door is/isn't susceptible to wind damage?
23. When taking measurements, are you focused only on measuring or do you think about how this could affect the safety?
24. What are the critical cues that lead to decision making?
25. Where do you search for issues? Do you have any expectations? How do you make sure that other sites are also inspected?
26. What are some of the skill-based, rule-based and knowledge-based behavior involved in risk inspection?

27. Do you use any inspection methods other than visual to assess the risk? (for example knocking on wood)
28. How do you make a decision based on positive and negative factors? Do you give equal weight to both positive and negative factors?
29. How do you assess the risk associated with a metal, concrete and wooden roof?  
Can you please walk me through the steps?  
Go to PowerPoint (slide 3-10)
30. When you are on a roof top, what is the first thing that you look for?
31. Could you please divide the roof inspection task into several small steps?
32. If you see a cracked /bubbled roof, how do you conclude if the roof needs to be changed or not? What questions do you ask to accept/reject your hypothesis?
33. What will you do if the information from 2 sources contradicts?
34. I know that you do not do in depth structural analysis. But, how do you decide the threshold for your inspection? Is there a clear cut boundary?
35. Other than wind damage, what else do you look for, especially when you are assessing occupancy?
36. Go to PowerPoint (slide 11) – could you tell me what information you get from this placard?

#### Missile Exposure

37. How do you assess the risk in this scenario? What are the information that you look for? PowerPoint (slide 13, 15)
38. How do you decide if something could be a potential missile?

#### Occupancy

39. How do you assess occupancy? How do you relate envelop risk factors to occupancy factors?
40. How do you make sure that the recommendations you propose is feasible?
41. How do you develop a few hypotheses based on building envelop alone? For example based on the shape or age. (again ask about missing information)
42. How are your hypotheses and conclusions influenced by the purpose of the building?
43. How do you say if a building is old or not? How old is actually old for your purpose? Is it subjective?  
PowerPoint slide 16-17 – could you do an occupancy assessment in this condition?

#### Loss investigation report/past report/building codes/sketches

44. How does a loss investigation report help in risk assessment? (Do you compare the damages happened with the prediction you made to check if you called it accurately?)
45. In the event of a catastrophe, you might review the previous risk assessment report to check if the engineer called the damage accurately. How does this affect

- the risk inspection? (Will this make the engineer biased? Will he end up reporting everything?)
46. How do past inspection reports help in subsequent inspections? (Do you use the findings from past inspections directly in subsequent inspections? Why?)
  47. When you go to the same sight for a second inspection, do you use the previous report? If yes, does that bias your assessment?
  48. What if you were not the inspector for the first inspection?
  49. Describe an instance when a company followed the building codes but still, you observed flaws?
  50. PowerPoint (slide 14) – how do you use this information in risk assessment?

#### Novice Vs expert

51. Is there a difference between novice and experienced inspectors?
52. On average, how long an inspection survey would take (expert Vs novice, efficiency)?
53. When you started your career as a field engineer, what errors were you prone to? How has your inspection procedure evolved over time?
54. How often do you evaluate a site?

#### Tools and technology

55. What types of equipment do you use on site? (glass thickness gauge, micrometer etc...)
56. Do other tools like Google Earth assists you in risk inspection?
57. What are some of the unique methods or tools that you use for risk assessment? For example, do you have a checklist that you take to the site?
58. Might using a checklist bias your decisions?
59. What are the issues with the conventional evaluation techniques you use? What are the advantages? What changes do you want to see?
60. Could you describe one of your most challenging experiences as a field engineer?
61. How flexible is the inspection method? Do you have to stick on to all these things or do you have the freedom to deviate from the conventional technique?
62. What's your note taking technique?

#### Collaboration

63. How do you collaborate with others and make decisions together?
64. How do you communicate your findings with others?
65. How many people will be there in a risk inspection team?
66. How do you think collaborating with others can improve the efficiency of the risk inspection process?

#### Challenges/new technology

67. How do you inspect areas that are hard to access?



68. Do you or are you planning to use any technologies to reach areas that are hard to access?
69. How can the efficiency of current risk inspection method be improved?
70. If you got a chance to design a technology to assist you in risk inspection, what would it be?
71. How does this inspection survey help in underwriting?
72. Do you currently use automated technologies such as robots, drones and sensors for this task? What are the pros and cons of these technologies?

## Appendix C

### Consent Form for Study 1

#### **An Observational Study to Understand the Needs of Field Engineers**

##### **Description of the research and your participation**

I am Sruthy Orozhiyathumana Agnisarman. You are invited to participate in a research study conducted by Dr. Kapil Chalil Madathil and me. The purpose of this study is to understand the nature of insurance risk assessment survey and the needs of field engineers. I am conducting this research as a part of my doctoral dissertation work. I am thankful to you for letting me join you at the inspection site. This information letter will give you the details about the study protocol and you are welcome to discuss with me your questions and concerns.

Research team member, Sruthy Orozhiyathumana Agnisarman, will observe you at the risk inspection site. If you are comfortable, you will be asked questions while performing risk inspection tasks. If you allow me to do so, you will be audio and video recorded performing risk inspection. Photographs may be taken of the inspection site, if their policy allows that. You are welcome to tell me not to record at any point. In addition, you will be asked to conduct a post evaluation interview and focused group. These sessions will be conversational in style and will last for 30 minutes to two hours. You will be encouraged to talk freely. You may choose not to answer any questions you are uncomfortable with and stop the interview at any time. You will be asked to attend focus group session with other field engineers. Notes will be taken during the focus groups and they will be audio and video recorded, if you are comfortable with that. We ask that you respect the privacy of others in the group and keep the information shared private. You may refuse to answer or leave the discussion at any time if you become uncomfortable.

Please understand that we are not testing your personal capabilities. We are trying to understand your needs and the state of the art of risk inspection.

##### **Risks and discomforts**

There is the possibility for loss of confidential information, but we have minimized this risk by not revealing any of your personal identifiers publicly. Your personal identifiers and collected data will not be available to anyone other than the principal and co-investigators. Also, please understand that revealing sensitive information in a focus group session will result in others knowing personal or confidential details. Please be wary of revealing sensitive or confidential information during focus group sessions. You may also find this study to be intrusive.

##### **Potential benefits**

There are no known benefits to you that would result from your participation in this research. This research may help us to understand how to develop automation assisted risk inspection methods. My dissertation will be available at Clemson's Cooper Library and will be accessible to the public. Moreover, the findings from this study may be presented at conferences or published as journal articles. Vignettes from your responses may also be used in journal or conference articles. However, your identity will not be revealed.

### **Protection of confidentiality**

The captured data (audio, video and photographs) will be stored in a password-protected computer in the Fluor Daniel 326. The documents will be accessible only to the principal and co-investigators. Your identity will not be revealed in any publication that might result from this study. We will delete all these recordings by July 2018.

### **Voluntary participation**

Your participation in this research study is voluntary. You may choose not to participate and you may withdraw your consent to participate at any time. You will not be penalized in any way should you decide not to participate or to withdraw from this study.

### **Participant incentives**

You will be awarded a \$10 gift card upon study completion.

### **Contact information**

If you have any questions or concerns about this study or if any problems arise, please contact Dr. Kapil Chalil Madathil at Clemson University at 713-294-6499. If you have any questions or concerns about your rights as a research participant, please contact the Clemson University Institutional Review Board at 864-656-0636.

A copy of this form will be given to you.

## Appendix D

### Coding Schema and Rules

1. Demographic
  - a. Age: anytime they talk about their age
  - b. Education: anytime they talk about their education/training/certification
  - c. Location: anytime they talk about their location
  - d. Occupation: any time the interviewee talking about their current job position
2. Level of Experience
  - a. Experience: any time they talk about their work experience/years/number of surveys
  - b. Wind experience : anytime they talk about any relevant wind related work experience
  - c. Novice (performed by less experienced people): any time an interviewee talking about less experienced or novice inspectors.
  - d. Expert (very experienced inspectors): any time they talk about improving/learning from experience (over time)
3. Learning
  - a. Post catastrophic: anytime they talk about post-catastrophic/post-disaster inspection/loss investigation report
  - b. Lessons learned: any time the interviewee talking about or referring to something as lessons learned or learning exercise or retrieving any information/knowledge/memory acquired
  - c. Training: anytime they talk about getting training or providing training related to wind survey (method employed to provide initial knowledge to novice inspectors)
4. Information Source
  - a. Wind information: anytime they talk about wind speed, wind map, and wind zone
  - b. Building drawings: any time the interviewee talking about getting information from building sketches
  - c. Manufacturer information: any time the interviewee talking about manufacturing information like placard, labels etc...
  - d. Internet: any time the interviewee talking about looking up information online (google, google earth, google map, other websites etc...)
  - e. Past inspection report: any time the interviewee talking about past inspection reports/ inspections

- f. Building history: any time the interviewee talking about how the building was constructed and related factors (restoration etc.)
  - g. Guidelines: anytime they talk about the assumptions they take based on their guidelines (things that lead the inspectors to use the assumptions provided by the company)
5. Inspection process:
- a. Steps followed: any time the interviewee talking about the steps followed (for example, go to the roof top, take measurement, etc..)
  - b. Dimensions/taking measurements: anytime they talk about taking measurements (such as length, fastener spacing etc.) and measurement pattern (such as corner, field perimeter)
  - c. Non-visual methods: any time the interviewee talking about non-visual methods such as dragging their foot, knocking on wood, toilet plunger, uplift testing, moisture testing
  - d. Areas of focus: anytime an area of a building is inspected (windows, walls,, doors)
  - e. Unique technique/preference: anytime the inspector talks about a step or something that he/she normally does but it's not a step in their procedure.
  - f. Information offloading: any time the interviewee talk about checklist and note-taking
6. Building characteristics
- a. Age of the building: any time the interviewee talking about the age of the building or its components
  - b. Roof type: any time the interviewee talks about different types of roof like concrete roof, metal roof, tile roof, etc
  - c. Building occupancy: any time the interviewee talking about the things inside the building, and the building purpose.
  - d. Building location: anytime they speak about the location on a building being inspected
7. New technology:
- a. Type of new technology: any time the interviewee talking about drones/new technologies used for risk inspection (drones, ipad etc...)
  - b. New technology advantage: Any time the interviewee was talking about the advantages of new technologies
  - c. New technology disadvantage: any time the interviewee talking about the disadvantages of new technology
8. Damage:

- a. Forecasting Failure: any time the interviewee talking about failures/failure modes based on the results or conditions
- b. Water damage: any time the interviewee talking about damages due to flooding/surge. It could be any water damage.
- c. Missile: any time the interviewee talking about missiles/projectile
- d. Roof condition: any time the interviewee talking about the roof condition (wrinkle, leak, bubble, tear, peeling, faulty drains, ponding, leaking, debris and any qualitative condition of roof)

#### 9. Tools

- a. Wind tool/calculator: any time the interviewee talking about the wind tool or property tool (software) used to calculate the wind pressure
- b. Devices/tools: anytime they talk about a piece of equipment used for inspection

#### 10. Factors affecting decision making

- a. Cognitive process/skills: any time the interviewee talking about cognitive processes/skills, Decision making (any time the interviewee talking about making a decision or actually makes a decision), Judgement (any time the interviewee talking about their judgement/judgement call), inference, analytical skills, problem solving skill
- b. Biases and methods to avoid/minimize biases: any time the interviewee talking about different biases that would affect their inspection/decisions and the measures they take to minimize or avoid it or the steps they take to remain cautious about biases.
- c. Errors/mistakes and Method to fix/resolve/recover errors: any time the interviewee talking about the errors/mistakes an engineer make and the ways to overcome/recover from a mistake
- d. Assumptions/expectations: any time the interviewee talking about their expectations or any assumptions that they make based on their expectations or understanding (but, not based on the guidelines). If the interviewee is talking about any assumptions they take based on their guidelines, it should be coded as guidelines.
- e. Critical cues: cues that played important role in the inspection process/decision making
- f. Confidence: any time the interviewee talking about their confidence level in their decision or information available

- g. Trust: Anytime the interviewee talking about trusting the information (such as building sketches, Internet etc..) or people (contractors, clients etc..)

#### 11. Sensemaking framework

- a. Contradicting information: any time the interviewee talking about positive factors/negative factors or any pieces of information contradicting to each other
- b. Confirming information: anytime the interviewee talking about confirming one piece of information using another piece of information
- c. Initial cue: any time they talk about the first thing that they look at or the first step to develop the initial frame
- d. Questioning data: any time the interviewee talk about looking for reasons for something or questioning an existing condition or doubting the data/information
- e. Lack of information: any time the interviewee talking about not having information available to complete inspection (eg: unavailability of building drawings/manufacture information)

#### 12. Conventional inspection

- a. obstacle/challenges and disadvantages of conventional risk inspection: any time the interviewee talking about the challenges associated with wind survey or the challenges they face such as inability to access any part of the building.
- b. Advantages of conventional inspection: advantages of conventional risk inspection

#### 13. Loss expectancy report

- a. Recommendations: any time the interviewee talking about recommendations
- b. Feasibility: any changes or recommendations that is feasible to apply (if it satisfies the ratio criterion 1 to 10)
- c. Loss expectancy: anytime the interviewee talks about loss expectancy calculation, analysis, report etc

#### 14. Collaboration: any time the interviewee talking about collaborating with others/wind inspection team, clients or any experts

#### 15. Emergency preparedness: any time the interviewee talking about the client's emergency response/preparedness plan or back up plans such as generators etc...

#### 16. Needs: anytime the inspector talks about his/her needs or things he/she wishes s/he has

17. Rooftop equipment: anytime the interviewee talks about roof top equipment

**Code rules:**

1. Code by segments
2. Double and triple coding is acceptable. If you are assigning more than 3 codes (beyond holistic/attribute codes) to a segment, consider breaking up the segment if possible.
3. Use memos to indicate:
  - a. Text that you feel should be coded, but do not have a code for it
  - b. Potential future themes you see emerging or want to explore once all data is coded
  - c. Any other thoughts, notes you need to get down about what you reviewing and coding
4. Don't feel compelled to code every word or line of text. Be mindful of overall purpose of project

**Consensus**

1. Each person should code independently
2. After coding your documents meet with you partner to discuss your coding results
  - a. Discuss your coding for each segment
  - b. If you have applied the same code but are off by a full sentence or less in where you have started or stopped the segment designation – you are in consensus – but you must decide where to start and stop applying the codes in your final coding structure
  - c. If your coding is consistent (with consensus) indicate your final codes for that segment on one document
  - d. If you do not have the same codes applied to a segment of text you are not in consensus. This includes:
    - i. Applying different codes
    - ii. Omitting codes
  - e. As you go through the document discuss where your coding is not consistent and reach consensus about the final codes to apply to each segment. Indicate that you had to discuss and reach consensus on the specific code by marking it with an \* or highlighting it as specific color.
  - f. If you are not able to reach consensus for a specific segment, then indicate this on your document.
3. Use your memos within your consensus discussion!
4. Your final document should clearly indicate the final codes for each coded segment and segments and codes you had to discuss to reach consensus.



## Appendix E

### Checklist Developed

1. Inspection of surroundings:
  - a. Confirm the wind speed for this area
  - b. What is the exposure level (B, C or D)? You can use the drone to inspect the area.
  - c. Please observe the surroundings
    - i. Are there any potential missiles or any loose/untethered objects (trees, furniture etc.)?
    - ii. Are there any adjacent buildings or structures?
    - iii. Are there any elements from the adjacent building (eg: rooftop equipment or loose objects) that could be potential missiles for the building under question?
    - iv. Is the building subject to flooding?
2. Roof inspection:
  - a. What is the roof type?
  - b. Measure the underdeck fastener spacing, if the roof has a metal deck.
  - c. Measure the distance between joists
  - d. Please confirm how the roof is attached (adhered, mechanically fastened or a combination)
  - e. Please take roof dimensions and fastener spacing dimensions on rooftop.
  - f. Please inspect the roof flashing especially perimeter flashing.
  - g. Confirm that the roof has a parapet. If the roof has parapet, is it continuous?
  - h. Take the parapet height
  - i. Please observe the overall roof condition. Look for any damages such as
    - i. Bubbling
    - ii. Cracking
    - iii. ponding - inadequate slope and clogged drainage allows water to pond on a flat roof
    - iv. vegetation growth
    - v. debris
3. Rooftop equipment:
  - a. Are there any rooftop equipment?
  - b. How are the rooftop equipment attached to the roof deck? How do the fasteners and connections look like?
  - c. Is the equipment properly strapped down? Is the fan cowling attached properly to resist the wind load?
  - d. Are there any random unattended debris particles (nails, wooden planks etc.)?
  - e. Are there any signs of corrosion or deterioration?
  - f. Does the roof have skylights or rooftop garden?

- g. Are there any potted plants?
- 4. External wall/envelope inspection
  - a. Dock door
    - i. Are there any dock doors?
    - ii. Is the dock door impact rated and pressure rated?
    - iii. Is the dock door properly installed? How do the fasteners and connections look like?
    - iv. Look for any potential missile impact
  - b. Windows
    - i. Are the windows pressure rated and impact rated?
    - ii. Look for any potential missile impact
  - c. EIFS
    - i. Please observe the general EIFS condition
    - ii. Make sure that the EIFS is free from mildew or mold issues and cracks.
    - iii. Identify if there is any potential missile impact to EIFS
    - iv. Identify how a damaged EIFS can lead to water/flood damage inside the building

## Appendix F

### Consent Form for Study 2

#### **An investigation of the effect of context-based visualizations to enhance the situation awareness of risk engineers**

##### **KEY INFORMATION ABOUT THE RESEARCH STUDY**

**Voluntary Consent:** You are invited to participate in a research study conducted by Sruthy Orozhiyathumana Agnisarman and Dr. Kapil Chalil Madathil. Dr. Kapil Chalil Madathil is an assistant professor at Clemson University. Sruthy Agnisarman is a PhD candidate at Clemson University, running this study with the help of Dr. Kapil Chalil Madathil.

You may choose not to take part and you may choose to stop taking part at any time. You will not be punished in any way if you decide not to be in the study or to stop taking part in the study. If you choose to stop taking part in this study, the information you have already provided will be used in a confidential manner.

**Alternative to Participation:** Participation is voluntary and the only alternative is to not participate.

**Study Purpose:** The purpose of this research is to investigate the effect of context-based visualization strategies to enhance the situation awareness and to improve the performance of windstorm risk engineers. Risk inspection is the process of investigating various risk factors associated with an infrastructure system to limit the extent of damage in the event of an extreme weather condition. The visualization strategies we propose are expected to improve the performance of the risk engineers.

**Activities and Procedures:** You will be assigned to one of the study conditions (control or experimental conditions). You will be asked to complete a scenario in which you will be completing the inspection of a commercial building in a simulated environment.

You will be asked to complete a demographic questionnaire. Then the researcher will guide you to the laboratory and will give you a brief description of the study. Then you will be asked to perform the task, followed by a subjective questionnaire about the task to help us evaluate your situation awareness and workload.

Your eye movements will be tracked using a non-invasive eye tracker mounted on the computer.

**Participation Time:** The amount of time required for your participation will be approximately 90 minutes. You will be asked to come back within a week to complete

another simulated task following the same procedure. However, this will take only 45 minutes.

**Risks and Discomforts:** There are certain discomforts that you might experience if you take part in this research. They include feeling of discomfort from using the eye tracking equipment and possible eyestrain. You will be allowed to take breaks to rest, and you may quit the research at any time without penalty.

**Possible Benefits:** There are no known benefits to you that would result from your participation in this research. But, the potential benefit to the science is the development of visualization strategies to improve situation awareness of infrastructure engineers.

## **EXCLUSION/INCLUSION REQUIREMENTS**

In order to participate in this study, you need to have a civil engineering or construction science background. You have to be either a graduate student (with a bachelor's degree in civil engineering or related domains) or senior student (pursuing a bachelor's degree in civil engineering or related domains).

## **INCENTIVES**

You need to participate in both the first study and follow-up study to receive gift card. You will be awarded a \$20 Amazon gift card at the end of the follow up study.

## **EQUIPMENT AND DEVICES THAT WILL BE USED IN THE RESEARCH STUDY**

You will complete the study on a desktop computer. An eye tracking device will record your eye movements. The simulation will also record data about your interaction with the simulation.

Although highly unlikely, if you happen to feel uncomfortable in any way (dizzy, lightheaded, or nauseous) while using the eye tracker, notify the research team immediately. If you continue to experience any discomforts after the study, please contact your preferred healthcare provider and notify the research team.

## **PROTECTION OF PRIVACY AND CONFIDENTIALITY**

The captured data will be stored on a password-protected computer in Fluor Daniel, room 321. The documents will be accessible only to the principal investigator and the co-investigators. Identifiable information collected during the study will be removed and the de-identified information will not be used or distributed for future research studies. Your identity will not be revealed in any publication that might result from this study.

We might be required to share the information we collect from you with the Clemson University Office of Research Compliance and the federal Office for Human Research Protections. If this happens, the information would only be used to find out if we ran this study properly and protected your rights in the study.

## CONTACT INFORMATION

If you have any questions or concerns about your rights in this research study, please contact the Clemson University Office of Research Compliance (ORC) at (864) 656-0636 or [irb@clemson.edu](mailto:irb@clemson.edu). If you are outside of the Upstate South Carolina area, please use the ORC's toll-free number, (866) 297-3071. The Clemson IRB will not be able to answer some study-specific questions. However, you may contact the Clemson IRB if the research staff cannot be reached or if you wish to speak with someone other than the research staff.

If you have any study related questions or if any problems arise, please contact Kapil Chalil Madathil at Clemson University at 713-294-6499.

## Consent

**By signing this consent form, you indicate that you have read the information written above, are at least 18 years of age, been allowed to ask any questions, and are voluntarily choosing to take part in this research. You do not give up any legal rights by signing this consent form.**

Participant's signature: \_\_\_\_\_ Date:

\_\_\_\_\_

Print name of participant: \_\_\_\_\_

A copy of this form will be given to you.

## Appendix G

### SAGAT Questionnaires for First Trial

#### **SAGAT\_1**

Q1 Participant number

---

Q2 What is the wind speed of the location

---

Q3 What is the exposure category?

- B (1)
- C (2)
- D (3)

Q4 Did you see any water body in the vicinity of the building?

- Yes (1)
- No (2)

Q5 Did you notice any object/objects between the lake and the building?

- Yes (6)
- No (7)

*Skip To: Q7 If Did you notice any object/objects between the lake and the building? = No*

Q6 What is it?

- Potted plants (4)
- Satellite (5)
- Cinder blocks (6)
- Fire hydrant (7)

Q7 Is there any other building or structure?

- Yes (4)
- No (5)

*Skip To: Q11 If Is there any other building or structure? = No*

Q8 What is it?

---

Q9 What are some of the equipment on the rooftop of the warehouse building?

---

Q10 What missile impact do you expect on the window facing the warehouse?

- Satellite (4)
- Cement block (5)
- Gravel (6)

- Tree branch (7)

Q11 What is the wall facing the warehouse (north side wall) made of?

- Brick (3)
- Glass (4)
- EIFS (5)
- Wood (6)

Q12 Do you expect any water damage in the event of an extreme weather condition?  
How do you expect it to happen?

---

Q13 What type of damage do you expect by missiles?

---

## **SAGAT\_2**

Q1 Participant number

---

Q2 What was the under deck fastener spacing?

---

Q3 What was the spacing between joist welds?

---

Q4 What was the under deck and roof type used here?

- Steel under deck with built up roof (1)
- Asbestos under deck with built up roof (2)
- Steel under deck with TPO roof (3)



- Wood under deck with TPO roof (4)
- Aluminium under deck with TPO roof (5)

Q5 Did you see any fasteners on the rooftop (not under deck)?

- Yes (1)
- No (2)

*Skip To: Q7 If Did you see any fasteners on the rooftop (not under deck)? = No*

Q6 Does the fastener spacing meet code requirements? Explain.

---

Q7 Did the roof have any perimeter flashing?

- Yes (1)
- No (2)

*Skip To: End of Survey If Did the roof have any perimeter flashing? = No*

Q8 Did the flashing look fine?

- Yes (4)
- No (5)

*Skip To: End of Survey If Did the flashing look fine? = Yes*

Q9 What damage do you expect from this damaged flashing when there is a category 4 hurricane?

---

### **SAGAT\_3**

Q1 Participant number

---

Q2 Did you see any clogged drain?

Yes (6)

No (7)

*Skip To: Q5 If Did you see any clogged drain? = No*

Q3 How was the drain on the north side (left side if you are facing the building) of the building clogged?

---

Q4 What issues do you expect as a result of clogged drain?

---

Q5 Did you observe water ponding on rooftop?

Yes (1)

No (2)

*Skip To: Q7 If Did you observe water ponding on rooftop? = No*

Q6 What would be the possible reason for it?

Leaking pipe (4)

Clogged drain (5)

Improper slope (6)

Q7 Where do you expect high wind pressure on the roof?

Perimeter and corner (4)

Perimeter and field (5)

Field and corner (6)

Q8 Did you measure the parapet height?

Yes (17)

No (18)

*Skip To: Q12 If Did you measure the parapet height? = No*

Q9 What is the parapet height?

---

Q10 Does this height meet code standards?

Yes (1)

No (2)

Q11 Should this parapet be given credit for modifying wind pressure? Why or why not?

---

Q12 Is the parapet continuous?

Yes (1)

No (2)

#### **SAGAT\_4**

Q1 Participant number

---

Q2 Does the roof have skylights?

Yes (1)

No (2)

Q3 Does the roof have solar panels?

Yes (1)

No (2)

Q4 How is the antenna attached to the rooftop?

---

Q5 What will happen to the antenna on the rooftop in the event of a category 4 hurricane?

---

Q6 What other damages do you expect from this antenna?

---

Q7 What other object did you see in front of the dock door?

Antenna (4)

Exhaust fan (5)

Solar panel (6)

Cement blocks (7)

There was nothing (8)

*Skip To: End of Survey If What other object did you see in front of the dock door? != Exhaust fan*

Q8 How is this object attached to the roof?

---

Q9 What will happen to this object if there is a category 4 hurricane? What other damages do you expect from this object?

---

**SAGAT\_5**

Q1 Participant number

---

Q2 How many dock doors were present on the rooftop?

- 0 (4)
- 1 (5)
- 2 (6)
- 3 (7)
- 4 (8)

Q3 How many of them were impact rated? What code is the impact rating based on?

---

Q4 What are the potential damages do you expect for the dock door?

---

Q5 How many windows did you observe on the rooftop?

- 0 (4)
- 1 (5)
- 2 (6)
- 3 (7)
- 4 (8)

Q6 How many of them were impact rated? What code is the impact rating based on?

---

Q7 What are the potential damages do you expect for the windows? Explain for each window separately.

---

Q8 What are some of the consequences of damaged windows?

---

Q9 Does the external wall have EIFS finishing?

- Yes (1)
- No (2)

*Skip To: End of Survey If Does the external wall have EIFS finishing? = No*

Q10 How do you describe the general condition of this EIFS?

---

Q11 What could happen to this EIFS if there is a category 4 hurricane?

## Appendix H

### Performance Questionnaire for First Trial

Q1 Participant number

Q2 Please answer the questions on this page based on the first task you completed.

Q3 What are the different types of missiles you expect in the event of a category 4 hurricane?

Q4 What is the implication of the exposure level of this location?

Q5 Is there any potential for interior damage due to rain? How?

Q6 What is your recommendations to reduce the wind vulnerability of this site based on the things you observed?

Q7 Please answer the questions on this page based on the second scenario you completed.

Q8 How do you know if a roof is mechanically fastened or fully adhered? Is the TPO roof in the simulation mechanically fastened or fully adhered?

Q9 Were the fastener rows parallel or perpendicular to the roof ribs?

Parallel (1)

Perpendicular (2)

Q10 What are some of the issues you noticed on the rooftop?

Q11 How do you think these issues will cause further damages to the building in the event of an extreme weather condition?

Q12 Did you observe ponding on rooftop?

Yes (1)

No (2)

*Skip To: Q14 If Did you observe ponding on rooftop? = No*

Q13 What could be the possible reason for roof ponding?

Q14 What is the general condition of roof flashing? What kind of damages do you expect as a result of flashing failure?

Q15 What is the fastener spacing in perimeter, corner and field?

Q16 Where do you expect high wind pressure on rooftop? Why?

Q17 Please answer the questions on this page based on the third task you completed.

Q18 List the equipment you observed on the rooftop.

Q19 What is the equipment you observed on the north side of the rooftop (left side when you face the building)?

- Antenna (4)
- Duct work (5)
- Skylight (6)
- Chimney (7)

*Skip To: Q21 If What is the equipment you observed on the north side of the rooftop (left side when you face the... != Antenna*

Q20 What are the possible damages this equipment could cause? Why?

Q21 What are the issues associated with the air duct on the rooftop? Is it properly attached?

Q22 Does the fastening method used for this equipment meet the standard criterion for a building in high exposure area?

Q23 What would be your recommendations to the clients to reduce the wind vulnerability of this facility?

Q24 Please answer the questions on this page based on the fourth task you completed.

Q25 Is the dock door pressure rated?

- Yes (1)
- No (2)

Q26 What do you expect to happen to this dock door in the event of a category 4 hurricane?



Q27 Were the windows pressure rated? What is the advantage of using pressure rated windows?

Q28 Do you expect these windows to withstand a category 4 hurricane wind pressure? Why or why not?

Q29 Does the building have any kind of External Insulation Finishing System (EIFS)?

Yes (4)

No (5)

*Skip To: Q32 If Does the building have any kind of External Insulation Finishing System (EIFS)? = No*

Q30 How do you describe the general condition of EIFS?

Q31 What will happen to EIFS and the building in the event of a higher category hurricane?

Q32 What would you recommend to change about the windows, dock doors and EIFS to improve the wind resistance of the building?

Appendix I

SAGAT Questionnaires for Second Trial

**SAGAT\_1\_2**

Q1 Participant number

---

Q2 What is the wind speed of the location

---

Q3 What is the exposure category?

- B (1)
- C (2)
- D (3)

Q4 Are there any potential wind borne missiles in the building surroundings?

- Yes (4)
- No (5)

*Skip To: Q6 If Are there any potential wind borne missiles in the building surroundings? = No*

Q5 What are they? Select all that apply.

- Furniture (1)
- Antennae (2)
- Tree (3)
- Lamp post (4)

Q6 Did you see any water body in the vicinity of the building?

- Yes (1)
- No (2)

Q7 What furniture did you observe outside the hotel? Select all that apply

- Table (6)
- Bench (7)
- Chair (8)
- Lounge chair (9)

Q8 Is there any other building or structure?

- Yes (4)
- No (5)

Q9 Do you expect any water damage in the event of an extreme weather condition?  
How do you expect it to happen?

---

**SAGAT\_2\_2**

Q1 Participant number

---

Q2 What was the under deck fastener spacing?

---

Q3 What was the spacing between joist welds?

---

Q4 What was the under deck and roof type used here?

- Steel under deck with built up roof (1)
- Asbestos under deck with built up roof (2)
- Steel under deck with TPO roof (3)
- Wood under deck with TPO roof (4)

Q5 Did you see any fasteners on the rooftop (not under deck)?

- Yes (1)
- No (2)

*Skip To: Q7 If Did you see any fasteners on the rooftop (not under deck)? = No*

Q6 Does the fastener spacing meet code requirements? Explain.

---

Q7 Did the roof have any perimeter flashing?

Yes (1)

No (2)

*Skip To: End of Survey If Did the roof have any perimeter flashing? = No*

Q8 Did the flashing look fine? Explain.

---

Q9 What are the issues?

---

### **SAGAT\_3\_2**

Q1 Participant number

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Q2 Did you see any clogged drain?

Yes (6)

No (7)

*Skip To: Q6 If Did you see any clogged drain? = No*

Q3 How many clogged drains did you see on the rooftop?

1 (1)

2 (2)

3 (3)

4 (4)

Q4 How was it clogged?

---

Q5 What issues do you expect as a result of clogged drain?

---

Q6 Did you observe water ponding on rooftop?

Yes (1)

No (2)

*Skip To: Q8 If Did you observe water ponding on rooftop? = No*

Q7 What would be the possible reason for it?

Leaking pipe (4)

Clogged drain (5)

Improper slope (6)

Q8 Where do you expect high wind pressure on the roof?

- Perimeter and corner (4)
- Perimeter and field (5)
- Field and corner (6)

Q9 What are the parapet materials used? Select all that apply.

- Concrete (1)
- Glass (2)
- Wood (3)
- Fiber (4)

Q10 Did you measure the parapet height?

- Yes (17)
- No (18)

*Skip To: Q14 If Did you measure the parapet height? = No*

Q11 What is the parapet height?

---

Q12 Does this height meet code standards?

- Yes (1)

No (2)

Q13 Should this parapet be given credit for modifying wind pressure? Why or why not?

---

Q14 Is the parapet continuous?

Yes (1)

No (2)

### **SAGAT\_4\_2**

Q1 Participant number

---

Q2 Select the objects you saw on the rooftop.

Skylight (1)

Potted plants (2)

Barbecue grill (3)

Lamp post (4)

Q3 How is the big air duct attached to the rooftop?

---



Q4 What equipment did you see on the north side edge of the rooftop? (your left hand side when you face the building)

- Satellite (1)
- Air duct (2)
- Barbecue grill (3)
- Solar panel (4)

*Skip To: End of Survey If What equipment did you see on the north side edge of the rooftop? (your left hand side when you f... != Satellite*

Q5 How is this object attached to the roof?

---

Q6 What will happen to this object if there is a category 4 hurricane? What other damages do you expect from this object?

---

## **SAGAT\_5\_2**

Q1 Participant number

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Q2 How many dock doors were present on the rooftop?

- 0 (4)
- 1 (5)
- 2 (6)
- 3 (7)

4 (8)

Q3 How many of them were impact rated? What code is the impact rating based on?

---

Q4 What are the potential damages do you expect for the dock door?

---

Q5 How many windows did you observe on the rooftop?

0 (4)

1 (5)

2 (6)

3 (7)

4 (8)

Q6 How many of them were impact rated? What code is the impact rating based on?

---

Q7 What are the potential damages do you expect for the windows?

---

Q8 What are some of the consequences of damaged windows?

---

Q9 Does the external wall have finishing?

Yes (1)

No (2)

*Skip To: End of Survey If Does the external wall have finishing? = No*

Q10 How do you describe the general condition of this EIFS?

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Q11 How many skylights did you see on the north side of the building?

2 (1)

3 (2)

4 (3)

5 (4)

## Appendix J

### Performance Questionnaire for Second Trial

Q1 Participant number

Q2 Please answer the questions on this page based on the first task you completed.

Q3 What are the different types of missiles you expect in the event of a category 4 hurricane?

Q4 What are the factors that could influence the impact of these missiles?

Q5 Is there any potential for interior damage due to rain? How?

Q6 What is your recommendations to reduce the wind vulnerability of this site based on the things you observed?

Q7 Please answer the questions on this page based on the second task you completed.

Q8 How do you know if a roof is mechanically fastened or fully adhered? Is the TPO roof in the simulation mechanically fastened or fully adhered?

Q9 What are some of the issues you noticed on the rooftop? Explain what might have caused those damages?

Q10 How do you think these issues will cause further damages to the building in the event of an extreme weather condition?

Q11 What could be the possible reason for roof ponding?

Q12 What is the general condition of roof flashing? What kind of damages do you expect as a result of flashing failure?

Q13 Where do you expect high pressure on rooftop? Why?

Q14 Were the fastener rows parallel or perpendicular to the roof ribs?

- Parallel (1)
- Perpendicular (2)

Q15 Please answer the questions on this page based on the third task you completed.

Q16 List the equipment you observed on the rooftop.

Q17 What are the issues associated with the air duct on the rooftop? Is it properly attached?

Q18 Does the fastening method used for this equipment meet the standard criterion for a building in high exposure area?

Q19 What would be your recommendations to the clients to reduce the wind vulnerability of this facility?

Q20 Please answer the questions on this page based on the fourth task you completed.

Q21 Is the dock door impact rated?

- Yes (1)
- No (2)

Q22 What do you expect to happen to this dock door in the event of a category 4 hurricane?

Q23 Was the window impact rated? What is the advantage of using impact rated windows?

Q24 Do you expect the window to withstand a category 4 hurricane wind pressure? Why or why not?

Q25 Does the building have any kind of finishing?

- Yes (4)
- No (5)

*Skip To: End of Survey If Does the building have any kind of finishing? = No*

Q26 How do you describe the general condition of the finishing?

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