Context-Based Visual Aids to Support the Situation Awareness of Field Engineers Conducting Windstorm Risk Surveys

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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. This process is performed by a trained windstorm risk engineer who physically goes to a facility to assess the wind vulnerabilities associated with it. This process is highly subjective, and the accuracy of findings depends on the experience and skillsets of the engineer. Although using sensors and automation enabled systems help engineers gather data, their ability to make sense of this information is vital. Further, their Situation Awareness (SA) can be affected by the use of such systems. Using a between-subjects experimental design, this study explored the use of various context-based visualization strategies to support the SA requirements and performance of windstorm risk engineers. The independent variable included in this study is the type of context-based visualizations used (with 3 levels: no visual aids, checklist based and predictive display based visual aids). We measured SA using SAGAT and performance using a questionnaire. SA and performance were found to be higher for the predictive display and checklist based conditions. The findings from this study will inform the design of context-based decision aids to support the SA of risk engineers.

INTRODUCTION

In past ten years an average of 170 wind related fatalities were reported in the United States every year. In 2017 only 128 fatalities were reported ("NWS Analyze, Forecast and Support Office," 2018). Such wind related natural disasters as hurricanes, tornado and thunderstorm affect individuals, society and economy (Tokgoz, 2012). Property damage is one of the most important consequences of such natural disasters. In recent years hurricanes caused billions of dollars losses in property damage (Fernández, 2001). However, natural disasters are unexpected and unavoidable. So, it is important to improve the resilience of infrastructure system to protect it. To limit the extent of damage and to minimize disruptions, wind vulnerabilities need to be identified and mitigated (Smith, 2011). Insurance companies carry out routine inspections at their clients' facility to assess wind vulnerability to develop risk mitigation and management strategies. This process is known as windstorm loss prevention survey or risk inspection ("What is the Windstorm Inspection Program?," 1999). While this process is primarily qualitative, the results of the inspection depends on the skillsets of the engineers conducting this inspection.

A qualitative research investigating the sensemaking process of risk engineers identified some of the critical challenges faced by windstorm risk engineers. Lack of a standardized survey protocol, and individual differences lead to disparities in the results of outcome (Agnisarman, Khasawneh, Ponathil, Lopes, & Madathil, 2018). Experience level is an important factor that directly predicts the accuracy of the report produced by risk engineers (Agnisarman et al., 2018). Risk engineers are required to predict what is going to happen in the event of an extreme weather condition based on their assessment of the current state of the infrastructure. More specifically, novice engineers find it challenging to develop an accurate mental model of the future state of the infrastructure as they seldom receive feedback on the performance of the infrastructure in the future (Agnisarman et al., 2018).

Automated technologies have been in use to improve the performance of infrastructure inspectors (Agnisarman, Lopes, Chalil Madathil, Piratla, & Gramopadhye, 2019). Artificial intelligence based technologies can be used to augment engineers' decision making (Fenves, 1984). However, the engineers' skill to make sense of the information is vital. Intelligent decision systems need to be developed to support the needs of the users of such systems (Agnisarman et al., 2019). Operator performance in such systems is mediated by vigilance decrements, complacency and loss of situation awareness (Endsley, 1999; Endsley & Kiris, 1995).

Situation Awareness (SA) is defined as a three level construct with Level 1 SA involving perceiving elements in the environment, Level 2 SA involving comprehending these elements and Level 3 SA involving projecting the state of the environment into the future (Endsley, 1995). 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). Though the three level SA theory proposed by Endsley (1995) has been used extensively in other domains such as aviation, aircraft maintenance and medicine, few studies have been conducted in the domain of civil infrastructure inspection investigating the SA requirements.

This study proposes the use of context-based visual decision aids to support the SA requirements of engineers performing windstorm risk inspection. Specifically, we augmented context-based information to the risk engineers to support their SA while conducting windstorm risk inspection. The visualization aids were designed based on the principles proposed by Endsley (2016) to design for SA. In depth interviews were carried out to understand the SA requirements of windstorm risk engineers (Agnisarman, Khasawneh, Ponathil, Lopes, & Madathil, 2018). The insights gained from this interview guided our effort to develop context-based visual decision aids. The overall objective of this study is to understand the type of context-based visual aids that can be

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used to support the SA of windstorm risk engineers. Further, we also investigated the effect of these visual decision aids on the performance of risk engineers. While measuring performance of windstorm risk engineers, two aspects need to be considered: 1) their mental model about the future state of the infrastructure in the event of an extreme weather condition and 2) their ability to perceive and make sense of the elements in the environment to write an accurate report. This research explores the following research questions:

RQ1: What is the effect of various context-based decision aids on the SA of risk engineers?

RQ2: What is the effect of various context-based decision aids on the performance of risk engineers?

METHOD

Hypotheses

The following hypotheses were tested:

H1: SA increases when the type of visualization changes from no visual aid to a predictive display based visual aid.

H2: Performance increases when the type of visualization changes from no visual aid to a predictive display based visual aid.

Study Sample

This study was approved by Clemson University's Institution-al Review Board (IRB). We recruited 30 civil engineering/construction science and management junior, senior or graduate level students, ranging from 21 to 41 years old (M = 24.33, SD = 4.05)) for this study. More demographic information can be found in Table 1. This study sample was chosen to simulate the technical skills of actual windstorm risk engineers.

Table 1
Demographic characteristics of the participants

Variable (N = 30)	N	%
Gender		
Female	7	23.33
Male	23	76.67
Race		
White	16	53.33
Asian	11	36.67
Black/African American	2	6.67
Other	1	3.33
Major		
Civil Engineering	27	90
Construction Science	3	10
Degree Pursuing		
Undergraduate	13	43.33
Graduate	9	30
Doctorate	8	26.67

Apparatus

A Dell desktop computer was used to run windstorm risk inspection simulation. Participants completed the study in this simulated environment. Study questionnaires was administered using a Dell laptop computer through Qualtrics research suite (Qualtrics, Provo, UT).

Scenarios

This study used a simulation of an academic building located in a high wind exposure area developed using Unity game engine. The artefacts used in the simulation are designed based on the findings from a qualitative research carried out to investigate the sensemaking process of windstorm risk engineers (Agnisarman, Khasawneh, Ponathil, Lopes, & Madathil, 2018). The following roof components as suggested by Unanwa (1997) were used to develop scenarios in the simulation: 1) Roof covering, 2) Roof sheathing and roof frame, 3) Rooftop equipment, 4) Building envelope, 5) Structural system.

Experimental Design

Independent variable. This study used a one-way between-subjects design. The primary variable of interest was the type of context-based visual aid presented. This is a between-subjects variable with 3 levels:

1. *No visualization/control condition.* No context-based visual decision aids were presented to the participants in this condition. Participants walked around and assess the wind vulnerabilities.
2. *Checklist based.* This text-based visualization helped users perceive and gather information in the environment. An example of this type of visual aid is shown in Figure 1. This checklist prompts participants to notice and perceive cues in the environment.

- What is the wind speed for this area?
- What is the wind direction?
- What was the maximum wind speed experienced in this area had experienced?
- Please observe the surroundings
    - Are there any potential missiles?
    - Are there any adjacent buildings/structures?
    - Is the building subject to flooding?
    - What is the surface roughness?
    - Are there any loose/untethered objects?
- How old is the roof system?
- Observe if the building is partially closed or not.

Figure 1. Example of checklist based decision aid

3. *Predictive visualization.* This type of visualization includes the elements of checklist based visualization. In addition, this type of visualization contains an interactive display of the behavior of some of the critical components of the building in the

event of a hurricane causing severe damage (damage state 4 as defined in HAZUZ) (*Hazus Hurricane Model User Guidance*, 2018). An example of this type of visual aid is shown in Figure 2. This visualization type is expected to help the participants form a more accurate mental model of the future state of the building infrastructure.

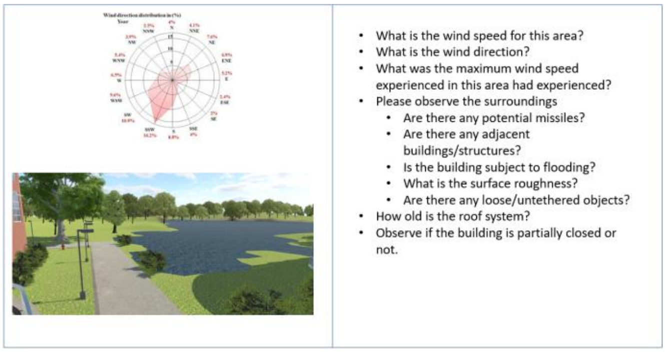

Figure 2. Example of predictive display decision aid

Dependent variable. The primary outcome of interest is the SA of the participants. SA was measured using the Situation Awareness Global Assessment Technique (SAGAT). SAGAT is a global measure based on the 3-level theory of SA proposed by Endsley (1995). This method measures the SA of the participants through a freeze probe protocol. As no SAGAT queries exist for infrastructure inspection domain, the questionnaire battery was developed based on the results of a previous qualitative research (Agnisarman, Khasawneh, Ponathil, Lopes, & Madathil, 2018).

The second outcome of interest is the performance of the participants. Though higher SA doesn't guarantee improved performance, there is a probabilistic relationship between SA and performance (Endsley & Garland, 2000). Participants' performance was measured using a questionnaire that is administered at the end of each task. This questionnaire was developed based on the scenarios used and was validated by a subject matter expert.

Procedure

This study started with the participants completing a demographic questionnaire. Then the participants were exposed to a training session during which the participants were given an overview of windstorm risk inspection process. The training was administered using a pre-recorded video explaining the windstorm risk inspection process. The participants were then asked to complete a training scenario to get used to the simulation and control commands. They were given instructions about the freeze probe SAGAT tool. Then the participants were randomly assigned to one of the study conditions. The participants completed all the assigned tasks in the virtual environment. After each task, the simulation froze to administer SAGAT query. However, they were not told in advance the exact time at which we administer the SAGAT questionnaire. The participants then completed a performance questionnaire. Participants were then debriefed to understand their metal model about the current state and future state of the infrastructure.

Analysis

Data was analyzed using the statistical packages available in R programming language. Outliers were identified and eliminated using Standardized Deviance residuals. Participants' response to SAGAT query and performance questionnaire was analyzed using one-way ANOVA.

RESULTS

Situation Awareness (SAGAT)

The response to the SAGAT questionnaire was coded as 0 (incorrect) and 1 (correct). SAGAT questionnaires were administered at 5 different time points. The cumulative SAGAT score was calculated and the percentage of correctly answered questions was calculated. The normality of the data set was tested using the Shapiro-Wilk test. Performance score was normally distributed for the checklist groups, as assessed by Shapiro-Wilk's test ($p > .05$). The Shapiro-Wilk test was significant for the control condition and predictive display condition. However, the data were normally distributed as the skewness and kurtosis values were with +/-3. There was only one data point with a residual value not within +/-3. This data point has a residual value of -3.03. So, this data point was kept in the analysis. There was homogeneity of variances, as assessed by Levene's test of homogeneity of variances ($p = 0.512$). A between-subjects one-way ANOVA was carried out to determine if the SAGAT score percentage was different for different experimental conditions. Performance score was statistically significantly different between different experimental conditions, as illustrated in Figure 3, $F(2, 27) = 17.25$, $p < 0.001$, $\omega^2 = 0.520$. Benjamini-Hochberg post hoc analysis revealed that significant differences in SAGAT score percentage were observed between predictive display condition ($M = 80.00$, $SD = 14.63$) and control condition ($M = 47.83$, $SD = 9.61$), $p < 0.001$, and checklist condition ($M = 71.30$, $SD = 13.24$) and control condition, $p < 0.001$. However, no significant difference was observed between checklist condition and predictive display condition.

Performance

Response to the performance questionnaire was graded and the cumulative score was calculated for each participant. The maximum score a participant could score was 56. The normality of the data set was tested using the Shapiro-Wilk test. Performance score was normally distributed for the control, checklist and predictive display groups, as assessed by Shapiro-Wilk's test ($p > .05$). There were no outliers, as assessed by examination of standardized residuals for values greater than +/- 3; and there was homogeneity of variances, as assessed by Levene's test of homogeneity of variances ($p = 0.304$). A between-subjects one-way ANOVA was carried out to determine if the performance score was different for different experimental conditions. Performance score was statistically significantly different between different experimental conditions as illustrated in Figure 4, $F(2, 27) = 6.961$, $p = 0.0037$, $\omega^2 = 0.284$. Benjamini-Hochberg post hoc analysis revealed that significant differences in performance score were observed between predictive display condition (M = 42.90, SD = 5.73) and checklist condition (M = 35.0, SD = 9.13), p = 0.035, and predictive display condition and control condition (M = 30.85, SD = 6.73), p = 0.003.

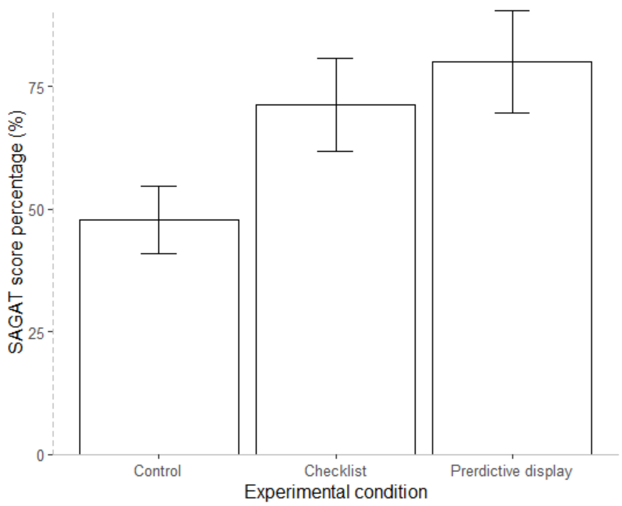

Figure 3. Effect of experimental condition on SAGAT score

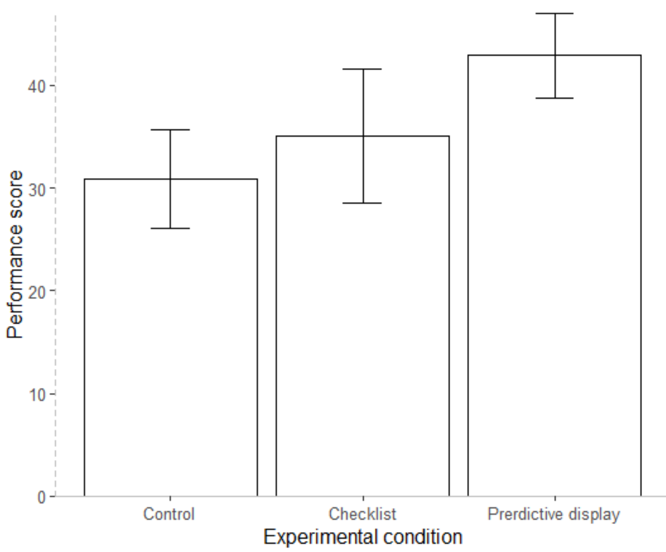

Figure 4. Effect of experimental condition on performance

DISCUSSION

This study investigated the effect of various context-based visual decision aids on the SA of windstorm risk engineers. The study used a between-subjects study design with one independent variable (type of context-based decision aids). The outcome variables of interest were the SAGAT score and performance score.

Participants who received the checklist and the predictive display condition had higher SAGAT score than the participants who completed the task in control condition. Though the SAGAT score was not significantly higher for predictive display condition, compared to checklist condition, the SAGAT score was consistently higher for predictive display condition, indicating that the elements of the predictive display condition supported the SA requirement of the participants.

The checklist condition helped participants to be vigilant and investigate various aspects of the building thoroughly. The checklist condition directly played an important role in acquiring Level 1 and Level 2 SA. The participants were cued to investigate and perceive various issues and problems in the building. In addition, the items in the checklist also helped the participants understand the interaction among various components in the infrastructure system. For example, the building simulation had faulty perimeter flashing system. Participants in the control condition failed to notice it. However, participants in the checklist and predictive display condition noticed this issue as they were asked to look for faulty flashing. In addition, participants in the predictive display condition were better equipped to predict the consequences of having a faulty perimeter flashing system. They were able to accurately predict various issues associated with fault perimeter flashing system such as water entry and roof tear. The predictive display condition showed a hypothetical scenario of a category 4 hurricane causing damages to the building. Participants exposed to this condition were able to develop better Level 3 SA as they were shown what could happen if there is a category 4 hurricane.

Further, the participants in the checklist condition and predictive display condition had a higher likelihood of perceiving cues in the environment, which directly influenced their Level 1 SA. For example, participants in the checklist condition and predictive display condition were explicitly asked to look for missiles. They were also asked to look for any other potential missile impacts such as objects from the rooftop of other buildings. However, participants in the control condition failed to notice the other building and potential missile impact from the other building. Another study in the domain of surgical safety investigated the effectiveness of an intervention involving procedural checklist on surgical team's SA. Though the results were not statistically significant, the teams exposed to the checklist condition reported higher SA in a subjective (Calland et al., 2011). Since Level 1 and Level 2 SA information was presented directly in the checklist condition and control condition, the SA of the participants was higher in these conditions (Endsley, 2016).

Use of checklist to assist complex tasks has been proven to have a positive effect on user performance and human error reduction (Hales & Pronovost, 2006). In addition, there is a probabilistic relation between situation awareness and performance (Endsley & Garland, 2000). In this study we observed higher performance for participants in the experimental condition. Though, the performance was not statistically significantly higher for checklist condition compared to control condition, a statistically significant positive performance difference was observed between control condition and predictive display condition. This higher performance can be attributed to higher situation awareness. Further, the checklist items and the information presented in the predictive display may have helped the participants to form a more accurate mental model of the current and future state of the infrastructure system leading to higher performance.

The participants were asked about their experience during the retrospective think-aloud session. None of the participants had any relevant previous experience in the domain of windstorm risk inspection. Participants who received the checklist found it useful. Further, some participants in the control condition mentioned that having a procedural checklist would have helped them perform better. They also said that they forgot to do some important tasks such as measuring fastener spacing and parapet height. Having a checklist would have helped them remember these seemingly trivial tasks. Further, participants in the predictive display condition mentioned that the predictive visualization of the future state of infrastructure helped them visualize the interaction between various elements in the infrastructure system. Although the SA of participants in the predictive display condition was not statistically significantly higher than checklist only condition, participants really liked the interactive visualization. They also said that the predictive display may be only useful during the training period. However, they would like to use the checklist, if they were performing the windstorm inspection task in a real-world scenario.

Though this study was able to identify the pros and cons of different context-based visual decision aids, the research is not without limitations. The study was not carried out with real windstorm risk engineers. Instead, a convenient sample of civil engineering students was used in this study. Additionally, a subjective performance measure was used to measure the performance of participants. A post-test survey was used to measure their performance. The response to this questionnaire may not necessarily reflect their actual performance. However, measuring actual performance can be challenging in this application. Additionally, there is a need to use other subjective measures such as trust in automation and automation complacency potential to investigate how users perceive these technologies (Khasawneh, Rogers, Bertrand, Madathil, & Gramopadhye, 2019). Further, it is important to measure the workload imposed by these displays on the users (Agnisarman, Madathil, & Stanley, 2018).

CONCLUSION

This study examined the effect of various context-based visual decision aids on the SA of participants. Our findings highlight the importance of using a procedural checklist to improve the SA requirements of windstorm risk engineers. Further research needs to be carried out with a higher sample size to investigate the influence of predictive display on the SA of participants. In addition, future research efforts can use a multidimensional performance measure including a subjective questionnaire, time taken to complete the task as well as the area covered by the participants to obtain a more accurate measure of performance. Additionally, the insight gained from this study can be used to develop training strategies for windstorm risk engineers.

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