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Performance effects of imperfect multi-modal sensory cueing in a target detection simulation

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Abstract

Past research has shown that multi-modal sensory cues can reduce the workload of the user while simultaneously increasing performance capacity. This study looks to examine how performance is impacted in a multi-modal sensory cueing target detection task in which the cueing automation is imperfect. Twenty-seven undergraduate participants volunteered to take part in the present multi-modal sensory automation target detection task. The independent variables were trial (i.e., three five-minute trial blocks) and the cueing method (i.e., tactile, auditory or a combination of tactile and auditory cueing) used to assist visual search for target detection across three screens. Dependent variables included each participant's response time and rate of accuracy. Results illustrate a significant decrease in response in the final trial when compared with the first trial. Results also illustrated a decrease in response time in each successive trial compared with the previous, each reflective of learning effects. A one-trial block exposure (5 minutes) to imperfect automation resulted in a response time decrease of 24%, while a two-trial block exposure (10 minutes) resulted in a response time decrease of 38%. Errors of omission results showed significantly lower miss rates in the final trial block when compared with the first trial block. In addition, errors of omission were lower in each successive trial compared with the previous. A one-trial block exposure (5 minutes) to imperfect automation resulted in a decrease in misses of 45%, while a two-trial block exposure (10 minutes) to imperfect automation resulted in a decrease of 65% in such misses. Our results suggest that interchanging multi-modal cues create stronger learning trends in a human–automation system than uni-modal cues. Results also showed that in spite of the automation used, automation failure resulted in a significant performance decrement. Auditory automation cueing failure produced a sevenfold increase in response time, while tactile automation cueing failure and a combination of auditory and tactile automation cueing failure produced a fourfold increase in response time. A speed–accuracy trade-off is not the cause of these results, because auditory automation cueing failure produces a twofold decrease in accuracy, and a combination of auditory and tactile automation cueing failure produced a threefold decrease in accuracy.

Keywords

Auditory cueing, tactile cueing, imperfect automation, target detection, visual search

I. Introduction

Automated tasks have become commonplace in today's society. According to Lee and See,¹ automation "actively selects data, transforms information, makes decisions, or controls processes." Imperfect automation has been described as automation that has limitations of which its designer is aware.² Although the designer of a system may be mindful of the system's limitations, such as how environmental conditions can affect performance, and how

these limitations affect the reliability of the system, such limitations may not be readily apparent to the operator of

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the system. This unreliability can lead to problems such as reduced situation awareness, over-reliance, complacency and mistrust.^{3,4} If an operator of such a system is not aware that a given system is not perfectly reliable, they will likely continue to use the system as if it were reliable, which would result in poor performance. Imperfect automation may result in an immediate performance decrement; however, once the operator becomes more experienced with the imperfect automation, they often adjust their level of trust and performance accordingly.⁵ For example, participants performing a target detection task with unreliable automated cueing improved their performance significantly once they became aware of the imperfect automated cueing.⁶

Often operators are required to visually monitor several screens at once over an extended period of time to spot signals. These vigilance-type tasks impose high workload demands on the operators. The addition of automated cueing to assist the operator in detection tasks can improve the salience of the targets; however, vigilance decrement may occur.⁷ An automated cue can fail to perform in one of two ways: it may fail to notify the operator when an event is present (a miss) or it may give false notification when there is no event present (a false alarm). Of the two failure types, misses are considered to be more detrimental to overall performance than false alarms.⁸

When the primary task is presented visually, adding auditory and tactile cues can aid in such detection performance. Different modalities use different attentional channels, and therefore do not necessarily compete for cognitive resources.^{9,10} Information presented in different modalities can be processed separately, which can increase processing bandwidth,¹¹ and promote problem solving.¹² In studies simulating target detection tasks, the use of additional modalities to present information to operators resulted in improved response time while locating threats, providing an overall performance improvement.¹³ Hancock et al.¹⁴ have reported evidence that information is processed more quickly and more efficiently when cues are provided in other modalities. In addition, when participants in a driving simulation task were provided with directions multi-modally, their response time was 15% faster than a baseline condition.¹⁵

Auditory cueing has decreased effort and improved performance on a multi-screen target detection task,¹⁶ as well as improved detection rates and lowered detection times.¹⁷ However, the capacity of the auditory system itself is limited. Pilots reported higher situational awareness during trials where the auditory workload was lower and adding tactile cueing to trials with high auditory loads improved performance.¹⁸ Tactile cueing is also beneficial in circumstances where visual communication may not be available or clear. Merlo et al.¹⁹ obtained promising results when augmenting visual displays with tactile cues. The addition

of tactile cueing in a target detection task has been shown to significantly decrease reaction time.¹³

In previous studies, operator performance (in terms of accuracy and response speed) improved as the operator gained experience with the imperfect automation.^{5,6} Our work presents two studies that explore the relationship between imperfect automation, multiple modes of automated cueing and performance. The objective of the first experiment is to establish whether comparable performance gains occur with cues that interchange between modalities. Thus, we hypothesize that in a mixed-modality cue setting with imperfect automation, participants' performance (as measured by response speed and accuracy) will improve with increased experience.

Imperfect automation in a monitoring task often results in missed targets, false alarms and an overall decline in performance. In certain task environments, this performance decline can be catastrophic. The objective of our second experiment was to present support that automation failure in the individual auditory and tactile automated cueing conditions will have more of a negative effect on performance compared with the combined cueing condition. Thus, our second hypothesis is that when automation is imperfect, single modality cueing will result in a greater performance decrement than combined cueing condition.

2. Simulator

To conduct these experiments we used a simulator, which incorporated a custom-built computer with three monitors and speakers, and a tactile belt made by Engineering Acoustics, Inc. (EAI). In addition, we used National Instruments LabView software to develop a program to synchronize video playback and automated cueing, as well as record performance measures. The National Instruments LabView software provided us with the ability to program the cueing automation and input video into the simulator. Figure 1 shows the experimental setup and simulation environment.

2.1 Cueing automation

Each participant participated in each of the three cueing conditions (i.e., tactile, auditory and combined of tactile and auditory). Automated cues and the presentation of stimuli were synchronized for each task, and were designed to guide the participants' attention to a specific screen. Tactile cues were 500 ms bursts of 250 Hz that took place in one of three tactors located on the participant's abdomen, each corresponding to an exact visual screen (i.e., left, right and center). The auditory cues were 500 ms 900 Hz tones emanating from one of three speakers at 50 dB, each mounted underneath a corresponding liquid-crystal display (LCD) screen.



Figure 1. Experimental setup and simulation environment. Shown are three monitors, with a speaker mounted below each, and a keyboard with a mouse. Also displayed are the tactile belt with battery and a reference sheet describing visual targets that appear on screens two and three.

Each participant was naive to the rate of reliability in the automated cues, which was 80% to guarantee that an automation failure event took place once for each task per trial. Automation error is when an event takes place and the participant is not alerted by the automation.

2.2 Experimental stimuli

Each scenario contained five targets on each of the three respective screens, for a total of 15 targets. Each screen presented a visual task and an “acknowledge” button. Screen one (left of center) presented a text messaging “chat room.” The participant was tasked with monitoring all text messages on screen one and was asked to click the “Acknowledge” button whenever a text message from “Bulldog 6” appeared on the screen. Screen two (center) presented a viewpoint of a driver traveling on a specific road. The participant was tasked with clicking the “Acknowledge” button whenever they saw a pre-specified route marker. Participants were told all other route markers should be considered non-targets. Screen three (right of center) presented a top-down map view that displayed symbols for friendly and hostile units, similar to a Blue Force Tracker system. The participant was tasked with clicking the “Acknowledge” button every time a symbol emerged on the map.

To ensure none of the participants identified a pattern, throughout each participant’s series of trials stimuli were presented at irregular intervals. Two steps were taken to address task difficulty and any potential asymmetric transfer effects. Firstly, all scenarios were assessed to match for difficulty level (medium level of demand) beforehand

and^{14,20} were counterbalanced. Although the concern of potential transfer cannot be addressed algorithmically, certain strategies can reduce its impact on outcome results.²¹ In our present experiment, participants were split into groups of nine and were assigned a different sequence of scenarios by cueing conditions.

3. Experimental method

3.1 Experimental participants

Twenty-seven undergraduate participants (6 male, 21 female) who were enrolled at a large university volunteered for class credit. Age for all participants ranged from 18 to 22 years ($M = 19.3$ years). Each participant completed an informed consent form before they participated.

3.2 Materials

3.2.1 Demographic information. We administered a demographic questionnaire to obtain pertinent information on participants (e.g., age, gender, education level).

3.2.2 Experimental apparatus. Apparatus in this experiment included a wearable EAI tacter belt with embedded tactile actuators, three Dell LCD video monitors and three Altec Lansing FX 4021 speakers. The embedded tactile actuators presented 250-Hz sinusoidal vibrations onto each participant’s skin through a contactor. When put around the participant’s body, the participant has an actuator over the umbilicus and one centered over their spine. Only three tacters were used, one on the umbilicus, one on the left and one on the right-hand side of the torso.

A LabView-based software program controlled and synchronized all displays and logged response times and accuracy. The center display was located directly in front of the participants, approximately 16 inches in front of their eyes. The other two displays were presented next to the center display, one on the left and one on the right. Each visual display presented a different visual search task.

3.3 Experimental design

The experimental design was a within-subject mixed-mode design. The independent variables were trial block/time (i.e., three five-minute trial blocks) and the cueing (i.e., tactile, auditory or combined tactile and auditory) used to aid visual search for target detection across the three displays.

The dependent variables included response time and accuracy rates. Possible errors included failing to acknowledge a target that appeared (miss), acknowledging a target

on the wrong display or acknowledging a target that did not occur (false alarm).

3.4 Procedure

The experiment was conducted in a competing noise- and vibration-free controlled laboratory environment. Before beginning the procedure, participants were briefed on their role in monitoring the three video displays and signed appropriate informed consent forms. Participants were trained on how to use a mouse to physically click the “Acknowledge” button on the respective displays that presented each pre-specified target. All participants were asked to respond as quickly and as accurately as possible. In addition, to assist participants in properly identifying each target cue before responding, participants were shown representative examples of each target. Lastly, all participants were familiarized with each augmenting cue and how they related to the three visual displays in front of them.

Participants were not aware of the associated reliability rate of any automated cues. Upon completing the instructions, participants completed a practice session to familiarize themselves with the simulator. After completing their practice trial, participants started the experimental trials. Each trial block was 5 minutes in length. Each time participants completed a trial block, they then completed a workload assessment questionnaire. After the participants completed testing, they were debriefed and departed the laboratory.

4. Results

The present experiment assessed objective performance capacity for both independent variables through three dependent measures: response time (the latency between the onset of the stimulus and the proceeding depression of the “acknowledge” button), response omissions (misses) and false alarms .

4.1 Response time by trial block

A paired-samples *t*-test was conducted to examine the response time between the three trial blocks. Results revealed a significant difference in the response times between the first trial block ($M = 4.36$, $SD = 4.47$) and the last trial block ($M = 2.67$, $SD = 1.20$), ($t(26) = 2.173$, $p = 0.011$). Response time was significantly faster in the third trial block compared with the first trial block. There was no significant difference in response times of the first and second trial blocks, and the second and third trial blocks, $p > 0.05$. Figure 2 illustrates that response time improved with each subsequent trial (i.e., first trial block = 4.36 s, second trial block = 3.30 s and third trial block = 2.67 s).

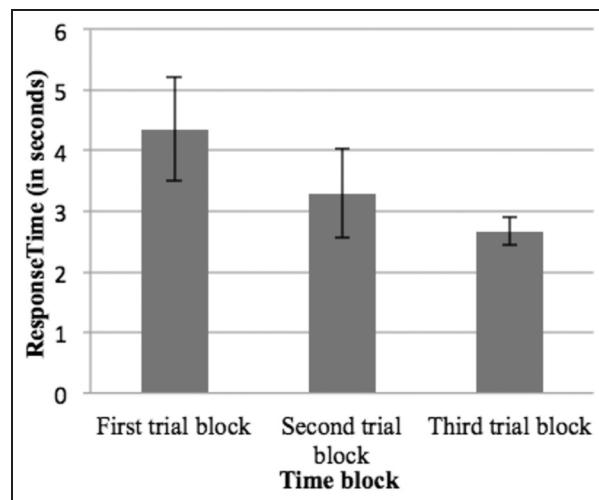


Figure 2. Response time by trial block.

A one-trial block exposure (5 minutes) to imperfect automation caused a 24% decrease in response, while a two-trial block exposure (10 minutes) to imperfect automation caused a 38% decrease in response time.

4.2 Error rate by trial block

A paired-samples *t*-test was conducted to examine missed stimuli between the three trial blocks. Errors of omission or misses significantly reduced in the third trial block ($M = 0.26$, $SD = 0.45$) compared with the first trial block ($M = 0.74$, $SD = 1.02$), ($t(26) = 2.229$, $p = 0.035$). Figure 3 shows that errors of omission decreased across subsequent trial blocks (i.e., first trial block = 0.74, second trial block = 0.41 and last trial block = 0.26). A one-trial block exposure (5 minutes) to imperfect automation resulted in a 45% decrease in misses, while a two-trial block exposure (10 minutes) to imperfect automation resulted in a 65% decrease in response misses. There proved to be no significant difference between false alarms for any of the trial conditions.

4.3 Response time by automated cueing type

A paired-samples *t*-test was conducted to compare response time between automated ($M = 1.54$, $SD = 0.44$) and non-automated (automation failure) ($M = 6.02$, $SD = 2.06$) stimuli across all cueing conditions ($t(80) = 19.020$, $p < 0.001$). We found that response time when automated cues failed was significantly higher compared with when automated cueing was present. As Figure 4 shows, automated auditory cueing failure caused a fivefold decrease in response time (7.39 s versus 1.42 s), automated tactile cueing failure caused a threefold decrease in response time (4.97 s versus 1.51 s) and combined automated auditory

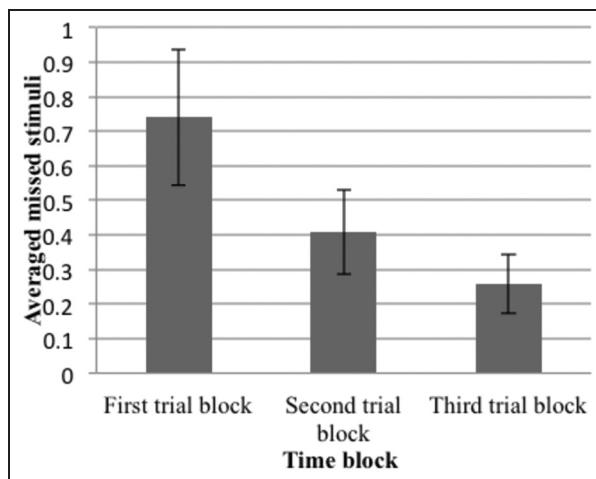


Figure 3. Error rate by trial block.

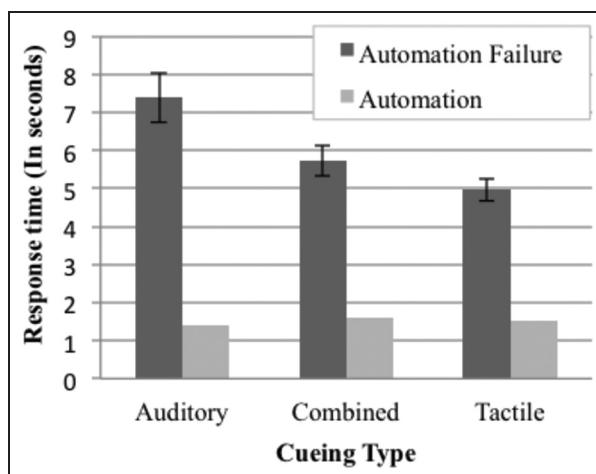


Figure 4. Response time by cueing type.

and tactile cueing failure caused a fourfold decrease in response time (5.71 s versus 1.60 s).

In addition to these evaluations, we examined automated cueing failure response time. A repeated-measure Analysis of Variance (ANOVA) showed a significant main effect, that is, $F(2, 52) = 10.765, p > 0.001$. Here results showed that the response times when automated cueing failed was significantly higher in the automated auditory cue condition and the combined automated tactile and auditory cue condition compared with the automated tactile cue condition (i.e., auditory cue = 7.39 s, combined cue = 5.71 s, tactile cue = 4.97 s). Post hoc comparisons using Fisher's least significant difference procedure revealed significant differences between failed automated auditory cueing and failed automated tactile cueing, in addition to the combined automated cue condition and the automated tactile cue condition. Figure 4 shows the overall

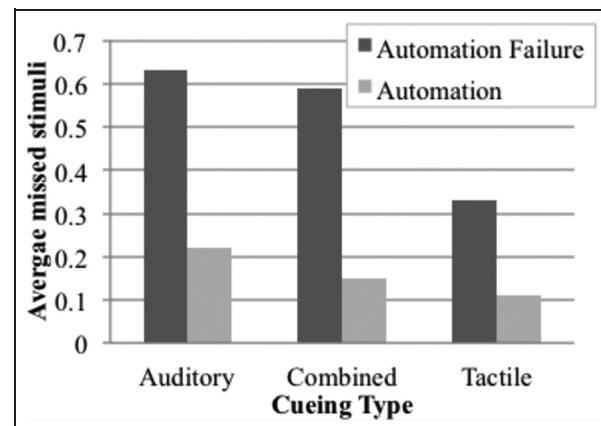


Figure 5. Error of omission rate by automation type.

response time benefit for any of the automated cueing conditions and the overall response times when automation failed by automation type. There proved to be no significant difference between the overall response times (cued and non-cued) for any of the three automated cueing conditions.

4.4 Error rate by automated cueing type

A paired-samples *t*-test was conducted to compare error of omissions (misses) between automated ($M = 0.16, SD = 0.43$) and non-automated (automation failure) ($M = 0.52, SD = 0.90$) stimuli across all cueing conditions ($t(80) = 3.382, p = 0.001$). Results show that misses were significantly higher when automated cueing failed. Automated auditory cueing failure caused a threefold decrease in accuracy (0.63 versus 0.22), automated tactile cueing failure caused a threefold decrease in accuracy (0.33 versus 0.11), and the combined automated auditory and tactile cueing failure caused a fourfold decrease in accuracy (0.59 versus 0.15). Figure 5 shows the overall error of omission rate benefit for any of the automated cueing conditions. There proved to be no significant difference between false alarms for any of the cued conditions.

5. Discussion

The present research investigated both the influence of experience gained throughout time and performance decrement based on modality in a target detection task. Each participant completed three five-minute trial blocks (auditory, tactile and combined cueing) in alternating order to mitigate any potential order effect.

To test our first hypothesis, we evaluated performance improvements through experience in mixed-modality cueing setting with imperfect automation to determine

whether speed and accuracy would improve with experience. Research has shown that when faced with imperfect automation, operators recalibrate their expectations and trust according to the performance of the automated device, thereby improving performance.^{6,22} The results confirmed that with each subsequent trial block, both response time and number of misses decreased, suggesting an increase in performance over time. Moreover, the results show a significant difference between the first and third trial blocks in both response time and number of misses. These results offer further evidence of the “first automation failure effect” proposed by Wickens and Xu,² which also showed improvements in performance in scenarios involving imperfect automation over time. Our results show that this effect occurs even when the modality of the automated cue is varied with each subsequent trial. Furthermore, these findings suggest that interchanging multi-modal cues create stronger learning trends in a human–automation system than uni-modal cues.

For the second hypothesis, we compared differences in performance decrement as a function of imperfect automation in scenarios that used a single modality (auditory or tactile) cueing, versus scenarios employing combined (auditory and tactile) cueing. Previous work by Hancock et al.¹⁴ has provided similar evidence for this hypothesis by showing improved performance in conditions using multiple modalities over conditions using only a singular modality. While our work also shows a significant difference in response time between the automation types when automation failed, there was no significant difference between automation types when automated cues were reliable. Here, the fastest reaction times for the imperfect automated cues were found in the tactile conditions. Some explanation for the superior performance in the tactile cueing condition can be found in a recent meta-analysis conducted by Lu et al.,²³ which investigated performance differences between tactile and auditory modalities. Their results showed that while complex information was responded to more quickly when it was presented as an auditory cue, participants responded to urgent interruption signals more quickly when presented in the tactile modality. Since our stimuli were not complex, it supports the previous finding that participants respond more quickly to an interruption signal presented via a tactile cue.

In addition to eliciting the fastest reaction times, the tactile cueing conditions also showed the fewest number of missed stimuli when automation failed and when automation was reliable. Moreover, the difference in number of missed stimuli was significantly lower for the tactile cueing condition than for either auditory or combined cueing in both reliable and unreliable automation cueing trials.

As would be expected, response time and accuracy both suffered in the conditions where the automation performed unreliably. The automation failure rate used here was only

20%, but it still significantly degraded performance. It is therefore of the utmost importance that automated systems be designed so as to perform as reliably as possible. However, it is understood that in real-world scenarios automated systems do not perform with perfect accuracy, so designs should be implemented in such a way to minimize over-reliance on automated cues. Future research efforts should ideally focus on designing systems that both maximize reliability of automated systems and minimize operator over-reliance on systems.

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Author biographies

Joe Mercado is a PhD student in the Modeling and Simulation: Human Systems program at the University of Central Florida. He is also a fellow of the Consortium Research Fellows Program working with the US Army Research Institute (ARI) for the Behavioral & Social Sciences. He recently completed working at the United States Military Academy in West Point as the Research Psychologist for the Engineering Psychology program. He obtained his BA in Psychology from Mercy College and holds a MS in Psychology from Mercy College. His primary research interests include multi-modality cueing and training and assessment in a technology-enabled learning environment. Joe is the President of the Society for Modeling & Simulation International, University of Central Florida Chapter (SCS-UCF) student chapter.

Timothy L White is a PhD student in the Applied Experimental and Human Factors Psychology program at the University of Central Florida. He is currently employed in the Dismounted Warrior Branch in the

Human Research and Engineering Directorate (HRED) of the US Army Research Laboratory (ARL). He has worked in the area of sensory performance, primarily focusing on the use of tactile displays systems as a means of communication for the dismounted soldier. He has also supported an immersive virtual environment system used for conducting controlled, laboratory-based investigations of soldier performance by modeling custom virtual environments, providing hardware support and performing data collection.

Tracy Sanders comes from an extensive background in fine art and graphic design, and continues to be especially interested in the role of aesthetic qualities in human factors research. She received her BS in Psychology in 2011, with a minor in Studio Art at the University of Central Florida. As an undergraduate, she studied trust in human robot interaction, time perception and three-dimensional studio art. She also holds an AS in graphic design from The Colorado Institute of Art. Now a PhD student in the Applied Experimental and Human Factors Psychology program at the University of Central Florida, she is a research assistant on the RCTA (Robotics Collaborative Technology Alliance) project, focusing her work on the aesthetic components of trust and robotics, and the physiological indicators of trust in human–robot interaction (HRI).

Julia Wright comes to Applied Experimental and Human Factors Psychology after a career in mechanical design engineering that included work in heavy industrial installations, appliance and automotive industries. During her time designing finish parts and assemblies for the appliance and automotive industries, she consistently strove to incorporate features into products that made them more user-friendly and intuitive for all consumer interactions from manufacture and assembly through to end-user. Wanting to better understand the psychology of design, she returned to school to earn her BS in Psychology from Grand Valley State University, focusing on cognitive psychology with a minor in applied statistics. As an undergraduate student, she worked on several research projects, including “the benefits of interruptions during complex task performance”. She is interested in memory and attention, visual attention, cognitive load distribution and human–technology interaction, particularly bridging the intuitive gap between humans and technology. One of her goals is to develop a cognitive psychology course specifically targeting the needs of engineering students to better prepare future design engineers. Julia is a Presidential Doctoral Fellowship recipient.

Peter A Hancock, DSc, PhD, is the University Pegasus Professor and Provost Distinguished Research Professor in

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