# The Role of Implicit and Explicit Systems Feedback in Return-to-Manual Performance

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE
UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Dr. Kathleen Harder

November 2018

**Acknowledgements**

I would first like to express my appreciation to my advisor, Dr. Kathleen Harder for the mentorship and guidance she has provided over the years. I left our countless discussions with new perspective and appreciation for the nuances of being human. Thank you for all the time and energy you invested into my development.

I would also like to thank my committee members, Dr. Thomas Stoffregen, Dr. Wilma Koutstaal, and Dr. Arathi Sethumadhavan for your assistance during this process and for the inspiration you fostered as professors. I hope to someday influence students as positively as you have influenced me.

To Dr. Michael Erickson, Jeannie Manzano, Dr. Katherine Aumer, and the students of Hawaii Pacific University, your gracious support allowed my family and I to relocate to paradise while still being able to continue my academic journey. Thank you for the use of the lab and the time and effort you expended supporting a visiting researcher. Special thanks to Chloe DePaola for her friendship and role as a research assistant on this project. Recruiting and running enough participants would not have been possible without your help.

Thank you, Mike Hurlburt for allowing me to use the basic logic and design of your nuclear power plant simulation. I found writing the code to customize and automate the simulation challenging and gained a deep respect for your design of a well-balanced dynamic system. The use of the simulation saved me countless hours of coding and effort.

Finally, I want to thank my employer, Barr Engineering Co. and director Dave Wilde for his flexibility and patience over the past four years. I could not have continued in the program without your support.

## Dedication

This dissertation is dedicated to my wife Jessica and son Colin. Thank you for the seemingly endless sacrifices you made to allow me to pursue my goals. I am looking forward to replacing the time once spent on school with time devoted to our family.

**Abstract**

Differences in display and automation types were examined to assess their influence on the development of novice-level participants' explicit and implicit understanding of a dynamic system. Participants operated a highly simplified nuclear power plant simulation for three simulation rounds; the first two rounds with the assistance of automated support and the third return-to-manual (RTM) round in which automated support was reduced. The combination of three Display Types (separable, configural, semantic-spatial) and two Automation Types (decision automation, no decision automation) resulted in a total of six unique conditions, with multiple performance, understanding, and workload measurements being employed. Results indicated the availability of decision automation improved performance and understanding, and reduced workload, but resulted in greater negative impacts associated with the loss of automated support in the return-to-manual round. Higher rates of errors occurred when attempting to address system damage in the RTM round for participants who previously operated the system with the assistance of decision automation and likely resulted from the availability of decision automation reducing participant experience operating the system in a damaged state. Examination of the influence of Display Types found the explicit feedback available within the semantic-spatial display improved the efficiency of meeting energy demand and reduced frustration when compared to the separable display but did not improve participants' understanding of the system. Decision automation appeared to negate differences between individual display type conditions, whereas distinct differences were found between no-decision automation conditions. Analysis of the predictive value of workload and understanding measurements found higher levels of implicit errors, better explicit understanding, and lower workload in simulation rounds one and two predicted smaller impacts on RTM performance. These and additional findings corroborate and extend previous research pertaining to relationships between automation, displays, understanding, and return-to-manual performance for novice participants.

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## Introduction

As societal dependence on dynamic systems (e.g., vehicle piloting, air traffic control, stock trading, power generation) continues to increase, so too does the need to ensure their effective management. To overcome human limitations and simplify the management of dynamic systems, designers use automation. Automation has shown great benefits for improving efficiency, safety, and effectiveness but has also been shown to negatively affect human performance by inducing complacency, affecting mental workload, skill degradation and reducing situational awareness (Parasuraman, Sheridan, & Wickens, 2000). When automation functions perfectly, these negative impacts may not be apparent. However, when automation fails or is unavailable and the operator is required to perform the procedure manually, the results of these effects may occur.

Research has demonstrated that an operator's ability to perform a task manually following automated assistance (return-to-manual performance) degrades as automation levels increase (Onnasch, Wickens, Li, & Manzey, 2014). The likelihood of this degradation occurring increases when decision making transitions from the human to automation (Onnasch et al., 2014). This effect can be attributed in part to the reduction of situational awareness (SA) and active processing that occurs when the operator transitions from actively managing the system to a more passive monitoring role (Endsley & Kiris, 1995).

Maintaining situational awareness at higher levels of automation has been shown to mitigate negative effects on subsequent manual performance (Onnasch et al., 2014; Wickens, Li, Santamaria, Sebok, & Sarter, 2010). However, three distinct levels of situational awareness confound researcher's ability to pinpoint the pertinent aspects of situational awareness's relationship with return-to-manual performance. Endsley (1988) defines three levels of situational awareness: Level 1 is the awareness of events occurring within the environment, Level 2 is the comprehension or understanding of the current situation, and Level 3 is the ability to predict what will occur in the immediate future. Endsley & Kiris (1995) found that subjects were able to effectively monitor the system and maintain Level 1 situational awareness at higher levels of automation, but their understanding (Level 2 SA) of what was occurring within the system suffered. This suggests Level 1 SA may not influence return-to-manual performance and focus should therefore be placed on the role of Level 2 SA. Level 2 SA assesses the operators understanding or comprehension of the current situation (Endsley, 1995). This understanding is a result of a cumulative awareness (Level 1 SA) of events that have occurred, combined with the operator's mental model or understanding of the system. For our purposes a mental model is the comprehension of variables within the system and the effects of control actions, and will be considered synonymous with the term "understanding" throughout this document (Neville Moray, 1999).

Many interventions have been proposed to improve operators' ability to maintain situational awareness, but few focus directly on improving Level 2 SA (Wickens, 2014; Wickens et al., 2010). One intervention that does is the use of displays designed to make it easier to understand what the automation is doing. This research explored how variations in displays (separable, configural, and semantic-spatial) influence the development of novice-level operators implicit and explicit understanding of a dynamic system. The differences between these displays investigated if graphical or text-based presentation of information improves mental model development, and how that mental model influences return-to-manual performance.

Three displays were tested with and without the aid of decision automation (Parasuraman et al., 2000). This focus was selected to investigate how automation influences mental model development at and below the critical level of decision automation, and if designing displays that improve understanding can fully or partially mitigate the negative effects decision automation has on return-to-manual performance. Two levels of automation presence (no-decision automation, decision automation) and three levels of display type (separable, configural, and semantic-spatial) were tested with a between-subjects factorial design. Assessments of participants' implicit and explicit understanding of the system were conducted, and various measurements of their performance and workload were performed.

The major objectives of this study were to investigate the following questions:

1. Does variation in automation type influence participants' explicit and/or implicit understanding of a dynamic system?
2. Does variation in display type influence participants' explicit and/or implicit understanding of a dynamic system?
3. Is there an interaction between display type and automation type that influences participants' explicit and/or implicit understanding?
4. Does participants' explicit and/or implicit understanding influence return-to-manual performance?

# Literature Review

## Automation

Systems pervade all aspects of human life. Physical systems such as power plants and vehicles, conceptual systems such as an organization or the economy, biological systems such ecosystems or the human body itself, and many others. These systems are not static and change continuously, making them dynamic. As dynamic systems become more complex, humans experience increasing difficulty understanding and controlling them (Diehl & Sterman, 1995). To reduce the complexity of managing dynamic systems, designers use automation. Automation is, "Any sensing, detection, information-processing, decision-making, or control action that could be performed by humans but is actually performed by a machine (N. Moray, Inagaki, & Itoh, 2000, p. 44)." This suggests that applying automation is not an all or nothing affair; it can be applied to the whole system or selectively to specific tasks at many different levels, ranging from fully autonomous task execution to offering minimal assistance. To better understand the diversity of methods and techniques that can be used in the application of automation, we must understand the capabilities of the human that the automation is intended to replace.

Parasuraman, Sheridan and Wickens (2000) define a four-stage model of human information processing meant to illustrate a simplified framework of human cognition. Sensory processing pertains to the detection, registration, and pre-processing of multiple sources of sensory information and occurs prior to full perception. Perception and working memory involves the processing of perceived and retrieved information in working memory, and also includes cognitive processes including rehearsal, integration and inference. Decisions are made in the third stage based on these processes. The fourth stage involves the implementation of a response based on those decisions.

| Stage | Stages of Human Information Processing | Stages of Automation |
|---|---|---|
| 1 | Sensory Processing | Information Acquisition |
| 2 | Perception & Working Memory | Information Analysis |
| 3 | Decision Making | Decision & Action Selection |
| 4 | Response Selection & Execution | Action Implementation |

Table 1. Stages of Human Information Processing and their corresponding Stage of Automation (Parasuraman et al., 2000)

The four stages of human information processing correspond to four stages of automation (Table 1). Automation of information acquisition refers to the sensation and registration of data. Information Acquisition can range from collecting raw data from sensors to the filtering, sorting, and highlighting of information important to the operator. Information Analysis is a more complex analysis and integration of the data collected. This can vary from the application of algorithms for purposes of forecasting or prediction to the integration and consolidation of multiple variables into a simplified view. In the Decision Selection stage, the automation makes recommendations or narrows the decision options. For example, expert systems apply complex conditional logic to varying scenarios and develop decision recommendations for the operator. The final stage is the automation of action implementation, where physical or logical action is carried out. This can be accomplished with the permission of the user or completely autonomously depending on the design of the automation. Parasuraman et al. (2000) jointly reference Information Acquisition and Information Analysis as "Information Automation" and refer to the third stage of Decision and Action Selection as "Decision Automation."

Each successive stage of automation is associated with an increase in the level of automation (LOA). The decision automation that occurs in a recommender or decision support system can be considered a higher level of automation than occurs in the information analysis stage, which in turn is higher than the automation of information acquisition. The four stages can also be divided into steps within each stage, and the combination of steps and stages are referred to as degrees of automation (DOA). Based on a previous scale developed by Sheridan and Verplank (1978), Parasuraman et al. (2000) further describe decision automation by defining ten distinct steps. In these steps the computer:

1. The computer offers no assistance: human must take all decisions and actions
2. The computer offers a completed set of decision/action alternatives
3. Narrows the selection down to a few
4. Suggests one alternative
5. Executes that suggestion if the human approves
6. Allows the human a restricted time to veto before automatic execution
7. Executes automatically, then necessarily informs the human
8. Informs the human only if asked
9. Informs the human only if it, the computer decides to
10. The computer decides everything, acts autonomously, ignoring the human (Parasuraman et al., 2000, p. 287)

The application of automation simplifies the management of complex systems by transitioning tasks or parts of tasks that were once completed by the human to the automation. Varying degrees of automation supplant corresponding stages of information processing and research has shown that the use of different degrees of automation can influence human performance differently (Onnasch et al., 2014; Wickens et al., 2010). To better understand these influences, we examine how humans are impacted by the application of different levels of automation.

### Automation's Impact on the Human Operator

Automation does not just replace human activity, but it fundamentally alters the work being performed. These changes are influenced by the degree of automation used, the stage of information processing the automation is displacing, the type of task being automated, and many other factors. With so many variables at play, calculating the impact each will have on human performance can be difficult. In an attempt to determine how human performance is affected, Parasuraman et al. (2000) defined four distinct but interconnected primary evaluative criteria to assess the impacts of automation on the human operator. These include complacency, situational awareness, mental workload, and skill degradation.

Highly reliable but imperfect automation can lead to the operator over-trusting the reliability of the automation and becoming complacent in their monitoring (Parasuraman et al., 2000). Complacency can result in a series of behavioral consequences that are insignificant when the automation is functioning correctly, but can have catastrophic results when the automation fails (Wickens, 1999). Highly reliable automation can improve operator trust, which may result in operators no longer monitoring the processes being controlled by the automation. This reduction or elimination of monitoring results in lower situational awareness, decreased comprehension of the state of the environment, and a diminished understanding of what the automation is doing. Short term disengagement from a process due to complacency can result in a temporary reduction in situational awareness, but complacency over longer periods can result in the loss of skill at performing the task manually. Complacency therefore influences each of the other three primary evaluative criteria and demonstrates the interconnectivity between situational awareness, workload and skill degradation.

According to Endsley (1988) situational awareness (SA) is defined as, "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future (p. 792)." SA can be divided into three levels (Endsley, 1995). Achieving Level 1 involves the perception of the status and dynamics of relevant elements within the environment. For example, in a nuclear power plant Level 1 SA would involve the perception of water levels, warning lights, and awareness of individual subsystems and their status. Level 2 SA is the comprehension of the current situation, and is based on the comprehension of the interconnectivity between individual Level 1 elements to form a collective understanding of the environment. A power plant operator needs to assemble the disparate bits of data from individual system variables to determine the health of the system and identify deviations from expected values (Endsley, 1995). Finally, Level 3 SA is the ability to predict the future status of elements in the environment, and is achieved through the awareness and comprehension of the state of the system elements (Level 1 & Level 2 SA). In a nuclear power plant, Level 3 SA could be considered using the awareness of the status of individual plant components and subsystems and the comprehension of the functional interrelation of these subsystems to develop an immediate expectancy of how the plant will perform.

Human workload changes when tasks transition to automation and when different levels of automation are applied. Workload is a complex concept, but operationally it is simply a ratio of the intensity or time required to complete tasks to the time available to complete them (Hendy, Liao, & Milgram, 1997). Well designed automation appropriately calibrates mental workload to the tasks being performed (Parasuraman et al., 2000). Poorly designed automation, however, can result in an imbalance between the task's requirements and operator's mental capacity. Designers may automate the entire task, relegating the human operator to a purely monitoring role thus resulting in operators having little to do and in turn a low mental workload. In some instances, poorly designed or "clumsy" automation can actually result in increased or unevenly distributed workload (Wiener, 1988). High workload or workload overload can result in heightened stress, and other negative consequences such as decreased accuracy, locking on to a single strategy, decreased use of mental strategies that require higher mental computation, and giving more important information sources more weight (Edland & Svenson, 1993). When high workload is experienced, humans may adapt by changing their processing strategy to reduce the amount of information they need to process or to increase the time available (Hendy et al., 1997). These changes in processing strategies can result in lower situational awareness. Endsley (1995) describes relationships between levels of situational awareness and workload as follows:

1. Low SA with low workload: The operator may have little idea of what is going on and is not actively working to find out because of inattentiveness, vigilance problems, or low motivation.
2. Low SA with high workload: If the volume of information and number of tasks are too great, SA may suffer because the operator can attend to only a subset of information or may be actively working to achieve SA, yet has erroneous or incomplete perception and integration of information.
3. High SA with low workload: The required information can be presented in a manner that is easy to process (an ideal state).
4. High SA with high workload: The operator is working hard but is successful in achieving an accurate and complete picture of the situation (Endsley, 1995, p. 53).

The last of the primary evaluative criteria for the effects of automation design on human performance is skill degradation. The transition of tasks to automation, and the change in the operator's role from performing to monitoring can result in a diminished capacity to perform the tasks that were once done manually. A significant amount of research has been done pertaining to the factors that influence skill retention and decay. Arthur's (1998) meta-analysis indicates that open-looped and cognitive tasks are more vulnerable to skill decay than their closed-loop and physical counterparts. This is particularly relevant to automation failure. By definition, automated dynamic systems operate in an open-loop environment and rely on the operator's understanding of the system and environment (SA) to appropriately intervene in a time of failure. The management of dynamic systems also typically consist of cognitive tasks, making them more susceptible to skill degradation.

### The Effect of Decision Automation on Situational Awareness and Return-to-Manual Performance

In a meta-analysis examining the human performance consequences resulting from varied levels of automation, Onnasch et al. (2014) found that in nearly all cases, routine system performance increased with higher degrees of automation (DOA). This improvement serves as an incentive for designers to use higher levels of automation to maximize performance. However, Onnasch et al. (2014) also found that performance after an automation failure requiring the operator to perform the task without automation (return-to-manual) suffered more as automation levels increased. This is referred to as the lumberjack analogy, in essence the higher the automation level the greater the fall in performance in the event of an automation failure. A key finding in the article identified a critical boundary between automation that supports information analysis and that supporting decision selection. When the DOA moves across this boundary, negative consequences of automation are most likely, suggesting that removing the human from decision making effects a critical element that supports their ability to recover from an automation failure (Onnasch et al., 2014).

The research of Onnasch et al. (2014) also revealed a significant negative relationship between DOA and SA. In the studies examined, situational awareness was assessed with methods such as SAGAT (Endsley, 1988), the Situational Awareness Rating Technique (Taylor, 1989), and the identification of mode errors or errors of omission or commission. Though the relationship was not found in every study, the two studies with the highest lumberjack trade-off

(Kaber, Onal, & Endsley, 2000; Manzey, Reichenbach, & Onnasch, 2012) were also two of the four studies with strong negative correlations between DOA and SA. This suggests when increased DOA results in a loss of SA, it may in turn result in a decrease in return-to-manual performance. The two studies that showed a positive correlation between SA and DOA also showed a weak positive or no correlation between DOA and return-to-manual performance, supporting previous findings that situation awareness serves as a mitigating factor against higher levels of automation on return-to-manual performance (Wickens et al., 2010).

In a separate study, Manzey et al. (2011) investigated how the use of automation during training of medical students and physicians impacted performance of an image-guided navigation procedure when automation was removed. The results indicated similar performance in terms of time and quality as those who were trained without the aid of automation when automation was removed. This surprised the authors and they attempted to explain that the automation provided information analysis and decision support but still provided access to what they described as the "raw data." They also posited that the automated blocking of dangerous or inappropriate actions could have served to stimulate their reasoning and improve their understanding of how to effectively perform the procedure. The authors, however, failed to note the role situational awareness may have played in their findings. SA levels were not different between the automation and no-automation groups.

As previously detailed, Endsley (Endsley, 1988) defined three levels of situational awareness: Level 1 is the awareness of events occurring within the environment, Level 2 is the comprehension of the current situation, and Level 3 is the ability to predict what will occur in the immediate future. The three distinct levels may influence return-to-manual performance differently, and these differences may in turn explain why removing the operator from the decision making process amplifies the negative effects of automation on the human operator.

Endsley & Kiris (1995) found that subjects' situation awareness was lower under fully and semi-automated conditions than under manual performance. The study found that the subjects effectively monitored the system and that Level 1 SA or the perception of the status of the system was unaffected, but Level 2 SA pertaining to their understanding and comprehension of the system was negatively impacted. They determined that the transition from active to passive processing was most likely responsible for the decrease in SA under automated conditions. The relinquishment of decision making responsibility to automation allows operators to transition from the active processing of feedback to a more passive monitoring role. Psychological and human factors research has demonstrated the benefits of active processing of information over passive processing (Cowan, 1988; Endsley & Kiris, 1995; Mueller & Oppenheimer, 2014; Slamecka & Graf, 1978). The Generation Effect is a well-studied psychological phenomenon (McDaniel, Waddill, & Einstein, 1988; Rosner, Elman, & Shimamura, 2013; Slamecka & Graf, 1978), which describes the improvements in recollection humans experience when conducting a task themselves rather than watching another agent do so (Wickens, 1999). This aligns with the general sentiment that, there is a benefit to learning by active and effortful involvement over the passive reception of the same information (Slamecka & Graf, 1978).

The benefit that active processing has on learning suggests that the diminished understanding associated with lower Level 2 SA could be attributed to a failure to learn. This is particularly applicable if a human has been trained exclusively in a supervisory mode (Endsley & Kiris, 1995). Multiple studies have found negative effects on manual performance when a human is initially trained with the aid of automation (Clegg, Heggestad, & Blalock, 2010; Kessel & Wickens, 1982; Shiff, 1983). Kessel and Wickens (1982) examined the effects of training in a supervisory mode versus a manual mode and the transference of those skills when modes are reversed. They found subjects who trained manually and were then asked to perform in a supervisory mode benefited from their initial manual performance, whereas those initially trained in a supervisory mode didn't benefit from that training when switched to a manual mode. A study by Shiff (1983), found that despite initial manual training, subjects who operated in a supervisory capacity of automation performed more poorly in terms of efficiency and speed than those who only operated the system manually when tasked with bringing the system under control. These findings support Moray's (1986) claim that if a human has been exclusively trained for supervisory control, it is not possible for them to immediately shift to a manual mode in the event of an emergency.

There is a great deal of evidence demonstrating the relationship between decision automation and reduced situational awareness. Participants' ability to maintain Level 1 SA at higher levels of automation suggests that Level 2 or a participant's understanding of the system influences return-to-manual performance. The reduction in active processing associated with decision automation may result in inferior learning impacting the human's understanding of the system and ultimately resulting in poorer return-to-manual performance.

**Designing Displays to Improve Understanding**

A number of interventions involving methods to maintain or improve situational awareness have been recommended to improve human performance in the event of automation failure (Wickens, 2014; Wickens et al., 2010). These methods include techniques that reduce complacency, calibrate user trust levels, make failures more salient, and restore active processing. Though these approaches may improve situational awareness, many do not focus directly on improving Level 2 SA. One intervention that focuses on improving Level 2 SA is to design displays that make it easier for humans to understand the automation's operation.

Interaction with an automated dynamic system typically occurs through a computerized display or user interface (UI). Variations in displays have been shown to influence human performance. For example, ecological interface displays (EID) have been shown to improve situational awareness over more conventional designs in some situations for nuclear process control (Burns et al., 2008). EID's were developed from studying techniques used by troubleshooters to solve problems and enhance feedback by showing relationships in the environment (Burns et al., 2008; Vicente, 1995, 2002). To design an interface that improves the operator's understanding, we must identify factors that influence human understanding of the functionality of dynamic systems.

Displays visually represent the underlying system through the use of charts, text, animations, and other elements. It is through the interaction with these external representations that an operator's understanding, or internal representation is formed (Hegarty, 2014). Mayer (2014a) states that understanding is "the ability to construct a coherent mental representation from the presented material" (p.20). This aligns with multiple understandings of a mental model. Moray (1999) says a mental model is the comprehension of the variables within a system and the effects of control actions. Butcher (2014) describes a mental model as an "internal representation of a learner's understanding of a system or process, including its overall function and the interactions and relationships between its various components" (p.197). According to Hegarty (2014) a mental model is an internal representation of a system.

To develop an understanding or mental model of a system three types of knowledge are required: structure/configuration, behavior, and function (Chi, Leeuw, Chiu, & Lavancher, 1994; Hegarty, 2014). Configuration knowledge represents a static mental model of the system; it defines the components of the system and how they are connected and spatially arranged.

Behavior knowledge requires an understanding of the causal chain within the system and how the components physically and temporally interact, and equates to a dynamic mental model of the system. Finally, a functional understanding of a system pertains to how the structure and behavior achieve what the system is designed to do.

Interface designs vary in how they represent the structure, behavior, and function of a system; these variations influence the formation of the human's internal representation. A high level functional understanding may be achieved through a simple description of the purpose the system is designed to fulfill. Development of a static mental model that represents the structure of the system may be achieved through diagrams that illustrate the location and layout of a system's components. Understanding the behavior of a dynamic system and how the components interact to develop a dynamic mental model are more complex and require feedback from the system. This feedback can vary in the information it contains, the format of the information, and the capacity of the human to interpret the information conveyed.

**Feedback**

Sterman (1989) argues that poor performance is a result of flawed mental models that develop from "misperceptions of feedback" provided by dynamic systems and that these models may be self-perpetuating because participants focus on inappropriate variables and relationships. He states that misperceptions of feedback stem from "a failure on the part of the decision maker to assess correctly the nature and significance of the causal structure of the system, particularly the linkages between their decisions and the environment" (Sterman, 1989, p. 324). And Diehl and Sterman (1995) found that participants attempting to manage dynamic systems fail to account for two aspects of dynamic complexity. The first is the misperception of time delays and the failure to appreciate the delay between the initiation of an action and the realization of its full effect. The second pertains to the misperception of feedback from decisions in the environment. Participants do not fully account for the positive and negative endogenous multipliers within feedback loops, which contradict decision processes based solely on an exogenous environment. Diehl & Sterman's (1995) research has shown that despite having access to all of the information needed to effectively control a system, participants failed to build dynamic mental models that accurately represented the behavior of the system. To begin to understand why humans fail to develop accurate mental representations, we must examine how different types of feedback influence learning.

Feedback can be classified in many different ways due to variations in its intentionality, delivery method, target and content (L. Bangert-Drowns, C. Kulik, A. Kulik, & Morgan, 1991). We examine two methods: corrective feedback that informs if a decision is correct or incorrect, and explanatory feedback that explains or provides insight into the principles behind why a decision is correct or incorrect (Atkins, Wood, & Rutgers, 2002; Moreno, 2004). Outcome feedback is a form of corrective feedback that communicates information about task performance such as a score, inventory level, etc. and is used to improve performance "on-line" throughout task participation as participants change decision processes to result in desired outcomes (Atkins et al., 2002; Gibson, Fichman, & Plaut, 1997; Johnson & Priest, 2014). If the change in score or outcome moves in alignment with the human operators' goals, they may perceive their decisions and control actions as correct. If the outcomes change in a way contrary to their goals, their behaviors may be interpreted as incorrect. Outcome feedback alone may fail to build complete mental models, due to the decision makers' failure to adjust their behavior to fully account for the task structure (Gibson et al., 1997). Participant focus on outcome feedback may explain the results in Diehl & Sterman's (1995) study. If decisions were based on the movement of inventory levels instead of the causal structure that dictated how those levels changed, participants may never achieve optimal results because they do not fully understand the behavior of the system. A dynamic system that only provides outcome feedback is in essence a black box. It provides no insight into the interworking of the system, only an action by the operator and a final result from the system. This may work for the management of simple systems, but additional feedback is necessary to build mental models that adequately represent the behavior of complex systems.

Explanatory feedback differs from corrective feedback by providing a principle-based explanation for why a decision was correct or incorrect (Johnson & Priest, 2014). Explanatory feedback reduces extraneous processing relative to corrective feedback by aiding the selection of appropriate information (Moreno, 2004). Systems feedback is similar to explanatory feedback. It provides insight into the interaction between components of the task system. An example of this is stock prices and confidence in the market, where a drop in stock prices can decrease market confidence, which in turn can lead to a further drop in prices (Atkins et al., 2002). System feedback permits insight into the interworking of the system by breaking it down into smaller subsystems or individual causal relationships, allowing the operator to implicitly deduce the rules through a series of observations, or explicitly understand them by determining their causal structure.

Meta-analysis has shown the superiority of explanatory feedback over corrective feedback for learning (Johnson & Priest, 2014; L. Bangert-Drowns et al., 1991). Bangert-Drowns et al. (1991) found that corrective feedback alone had minimal impact on learning (d = -.08), while explanatory feedback had a much greater positive effect (d = -.31). This suggests that when designing a user interface to maximize understanding, it may be insufficient to provide only corrective or outcome-based feedback, particularly for novice users attempting to learn the behavior of the system. Explanatory feedback in these studies was primarily provided through extended explanations or descriptions of why an answer was correct or incorrect. The question then becomes one of whether explanatory feedback must explicitly communicate why a decision was correct or incorrect, or can systems feedback be provided that requires the implicit deduction of these rules? To understand this question, we investigate the difference between implicit and explicit memory.

**Implicit and Explicit Knowledge**

Numeric and graphical feedback requires the operator to implicitly infer the relationships between components within a dynamic systems, whereas text based feedback can explicitly define these relationships. The top-down approach associated with explicit feedback may reduce extraneous cognitive load, providing additional resources to be applied to germane load and the development of a mental model of the system but there is no guarantee that the additional capacity will be reapplied. Alternatively, the bottom-up approach associated with implicit feedback may serve as germane load, requiring the inference of relationships between system components, but may increase mental workload. To understand which feedback format develops a superior mental model, the relationship between explicit understanding and implicit skill is examined.

Berry and Broadbent (1984) conducted a series of experiments examining the relationship between explicit verbalizable knowledge and performance on a system management task. Their first experiment found that practice increased performance but showed no effect on the ability to answer questions pertaining to the task. They then tested the effects of verbal instruction prior to the task, finding that it significantly improved the ability to answer questions but had no effect on performance. The final experiment examined the effects of concurrent verbalization asking the participants to think-aloud and justify their decisions. They found that concurrent verbalization did not have a positive impact on performance, but when concurrent verbalization was combined with verbal instruction prior to beginning the task, a significant improvement in control performance was found. Concurrent verbalization further improved verbalizable knowledge when combined with prior verbal instruction over verbal instruction alone. These findings demonstrate a difference between explicit verbalizable knowledge and implicit procedural skill and the benefits to both, when developed together.

In an experiment testing the relationship between the ability of a person to effectively perform a task and their ability to answer questions about that task, Broadbent et al. (1986) found that practicing the total task does not improve the ability to answer questions about it, but practicing the isolated relationships within the task does. The authors found the group who practiced separate relationships (S group) in the first trial had already learned as much as the group who practiced the total task did by the final trial. The (S) group not only experienced higher initial performance, but learning in this way also allowed them to answer verbal questions. The experiment demonstrated that practice improves performance without improving the ability to answer verbal questions. Practice on separate parts of the system increased both verbal knowledge and performance. The authors conclude that that study provides evidence of independent "databases" for implicit and explicit (verbal) knowledge, because performance in both measures can move together or not depending on the stimulus. These findings provide further evidence that differentiates the role of explicit and implicit memory.

Research investigating reasoning and memory supports the Broadbent et al. (1986) claim that there may in fact be different "databases" or systems at play that influence implicit and explicit knowledge. Sloman's (1996) examination of historical literature makes an empirical argument for two distinct but cooperative systems of reasoning; an associative system and a rule-based system. The associative system is said to, "encode and process statistical regularities of its environment, frequencies and correlations amongst the various features of the world (Sloman, 1996, p. 4)." Similarly to a statistician, it uses temporal and likeness associations to draw relational inferences. The rule-based system is symbolic in nature and, "tries to describe the world by capturing different kinds of structure, structure that is logical, hierarchical, and causal-mechanical" (Sloman, 1996, p. 6). The associative and rule-based systems are thought to be capable of mimicking computations performed by the other, but may vary in efficiency and reliability depending on the type of problem. The individual's knowledge, skill, and experience will influence if a single system, or the degree to which both systems are applied to a problem.

Further support for the role of different systems can be found in human memory research. Tulving (1985) denotes a ternary memory system classification scheme identifying procedural, semantic and episodic memory in a “monohierarchical” arrangement. Procedural memory is the lowest level of the hierarchy, containing semantic memory a single, specialized subsystem, which in turn contains episodic memory as a specialized subsystem. Each system is supported by the lower system(s) but has capabilities not possessed by them. This hierarchical description of memory systems aligns with the portrayals of the associative and rule-based systems of reasoning. The development of complex stimulus patterns associated with procedural memory can be argued as similar or equivalent to the encoding and processing of statistical regularities associated with the associative system of reasoning. The symbolic nature of the rule-based system of reasoning which attempts to logically define the structure of the environment again shows similarity with semantic memory’s construction of mental models that represent the state of the environment. Further similarity is found in Tulving’s (1985) claim that the expression of knowledge differs between the memory systems. Just as implicit knowledge must be expressed directly, semantic and episodic memory can be expressed explicitly through different behavioral forms, including verbalization.

The argument for two independent but cooperative systems provides insight into the performance improvements found when participants practiced and also demonstrated improved verbal knowledge. This suggests that practice may work to develop the statistical and temporal correlations necessary for the associative reasoning system, and that verbal knowledge is supported by the rule based system. When a mental model is reinforced by both reasoning systems, they operate collectively to improve performance beyond either system alone. The findings of Broadbent et al. (1986) that practice on parts of a task allow for greater performance and a greater ability to answer questions pertaining to the task suggests that implicit skill can be expressed explicitly when sufficient inference is achieved.

This evidence suggests that displays designed to support the development of both implicit and explicit knowledge result in superior performance over either alone. The evidence also suggests that explicit knowledge can develop from inferred implicit knowledge. If this is correct, then numeric, graphical, and text formats can each serve as systems or explanatory feedback that enhances a human’s explicit understanding of a dynamic system. However, the answer to whether explicit or implicit systems feedback develops a mental model that facilitates superior return-to-manual performance remains. Further investigation of how information design influences the development of mental models is warranted. The cognitive theory of multimedia learning will be explored.

## Cognitive Theory of Multimedia Learning

Designing displays and feedback that improve learning requires alignment with human cognitive capabilities. The multimedia hypothesis states, "people can learn more deeply from words and pictures than from words alone (Mayer, 2014b, p. 1)," and is based on a more fundamental hypothesis that information designed to be presented in ways that align with how the human mind works are more likely to lead to meaningful learning (Mayer, 2014a). The cognitive theory of multimedia learning is a theory of how people learn from words and pictures and is based on the assumed validity of three cognitive science principles of learning: dual channels, limited-capacity, and active processing (Mayer, 2014a).

The dual channels assumption posits that humans have separate channels for processing visual and auditory information and is based on Paivio's (1990) representation mode dual coding theory and the sensory-modality approach based on Baddeley's (1998) visuospatial sketchpad and phonological loop (Mayer, 2014a). Mayer (2014a) claims that information entering one channel may be converted to the other channel for processing. He provides an example of on-screen text being initially processed through the visual channel, but the mental conversion of those images to sounds results in processing through the auditory channel. The dual channels assumption can be leveraged to aid in the selection of display formats, suggesting that presentation of feedback through both channels may aid the development of mental representations.

Mayer's (2014a) second assumption is that each of these channels has a limited capacity and can only process a limited amount of information at one time. The amount of information held is measured by the ability to hold images or words in working memory. Determining how variations in displays will influence the cognitive load placed on these channels requires a background in the prevailing theory in training complex tasks. Cognitive load theory defines three environmental task demands that divide the limited cognitive resources of the learner (Paas, Renkl, & Sweller, 2003; Wickens, Hutchins, Carolan, & Cumming, 2012). Intrinsic load represents the fundamental complexity of a task and the interconnectivity between elements within the environment. The demands on working memory are inherent to the task being learned, thus intrinsic load can only be reduced by alteration of the task or by changing the knowledge level of the participant (Paas et al., 2003; Sweller & Paas, 2014). Extraneous or ineffective cognitive load introduces demands that are not intrinsic to the task and do not contribute to learning. An example of extraneous load is the diversion of working memory to activities such as search, where the learner must seek out needed information. Germane or effective cognitive load can also be influenced by the presentation of information but instead of interfering with learning, germane load enhances it (Paas et al., 2003). Germane load contributes to schema development and committal of material into long term memory where it is used to reduce demands on working memory as it is combined with additional schema. This additional working memory capacity can then be used to accommodate extraneous load or continue to build schemata through germane load. The application of cognitive load theory to user displays suggests designers should strive to maximize features that introduce germane load while minimizing extraneous load, without exceeding working memory capacity of either or both channels. Though conceptually simple, the difficulty comes in determining if design features will serve as extraneous or germane load.

The third assumption of the cognitive theory of multimedia learning is that humans actively engage in cognitive processing to develop mental representations (Mayer, 2014a). The cognitive processes involved in active learning are the selection of relevant material for transfer to working memory, the organization of that information into a coherent structure within working memory, and the integration of these structures with prior knowledge activated from long-term memory (Mayer, 2014a; Wittrock, 1989). The assumption of active processing aligns with our prior identification of the role active and passive processing have on return to manual performance.

Taken together, the three assumptions of multimedia learning suggest that displays should promote active processing, minimize extraneous cognitive load, and maximize germane load in both the visual and auditory processing channels without exceeding their capacity. If Meyer's (2014a) claim that text-based feedback is perceived through the visual channel but can be converted and processed through the auditory channel, then text may serve as an effective modality for systems feedback by conforming to all three assumptions of multimedia learning when combined with other forms of visual feedback. However, if text-based feedback is not converted and processed through the auditory channel, it fails to utilize both channels and may exceed working memory capacity for the visual channel when combined with additional visual feedback. The experimental design in this paper explores how text-based and other forms of visual feedback influence multimedia learning and seeks to generate further evidence that will support or discount the multimedia hypothesis.

**Multimedia Displays – Separable, Configural, and Semantic-Spatial**

Feedback from a dynamic system can be represented through a wide variety of formats, including but not limited to numeric, graphical, and text based representations. Each format exhibits unique characteristics that influence human performance. The selection of one or more of these formats is only the first step, designers must also determine how those formats will be integrated into a display. We explore three ways of designing displays using different visual formats: separable, configural and semantic-spatial.

### *Separable & Configural Displays*

Bennett & Flach (1992) define three ways a process can be mapped to a display. Separable designs display the "raw" data for each variable or sensor within the system individually. Integral displays map multiple variables to a single display, creating a new integrated identity while diminishing the identity of the individual variables. Configural displays map variables to elementary display features in a way that maintains the identity of the original variables while producing emergent features.

Providing individual data elements in a separable display requires the operator to infer the relationships between subsystems by maintaining the individual system variables in working memory. Separable displays may increase cognitive load by requiring humans to mentally integrate multiple sources of information. Ayres & Sweller (2014) describe this mental integration as extraneous cognitive load and that a negative impact on learning is likely. When the intrinsic complexity of the dynamic task is high, the increased extraneous load from a separable display may overload limited working memory.

An investigation into the Three Mile Island nuclear reactor incident found that while the information was available to the operators, no one could assemble the separate information to make the correct deductions (Woods, 1991). Looking to address these issues, Woods et al. (1981) investigated the use of a configural octagon shaped graph display to map sensor values used in nuclear power plants. The vertices were scaled resulting in the formation of a symmetrical geographic pattern during normal operation. When an abnormality developed, the pattern became distorted and lost its symmetry. This design was found to be very effective and was implemented in multiple nuclear power plant safety parameter display systems (Bennett & Flach, 1992). Configural designs have been shown to improve cue judgment, signal detection, and retrospective memory performance over separable displays (Bennett & Flach, 1992). However, little research has been done exploring how differences between separable and configural displays influence mental model formation of complex dynamic systems and how that that mental model affects return-to-manual performance.

To explore these questions we examine the difference in learning and performance when information is presented through tables and graphs. Tables can be considered separable displays as each data element is presented individually, while graphs may be considered configural if the visual combination of individual data elements result in emergent information that provides additional insight into the relationships between them. It is important to note that graphic visualizations are not always configural and can be considered separable if each variable is represented individually within a graph or chart. Studies have found improved performance in dynamic system tasks when graphical feedback is available (Atkins et al., 2002; Oron-Gilad, Meyer, & Gopher, 2001). Graphical displays allow for faster processing by shifting the load from the limited capacity of working memory to the higher cognitive capabilities of object perception and pattern recognition (Bennett & Flach, 1992). Atkins et al. (2002) suggest that graphical feedback may facilitate the acquisition of mental models by making the gain and delays within a dynamic system more salient, allowing the reallocation of the additional processing capacity to address the demands of the task. Interestingly, though they found that participants in the graphical group had better performance, the tabular group demonstrated stronger evidence of learning over successive trials. This suggests that graphical feedback may reduce intrinsic load allowing for greater performance, but the additional bandwidth is not reallocated to germane load.

The question becomes the following: If configural displays reduce extraneous cognitive load, is the cognitive capacity gained reallocated to germane features of the task resulting in an improved mental model and subsequent improved performance? Alternatively, does the additional cognitive load associated with the mental integration across multiple sources in a separable display serve in part as germane load, or is it extraneous load as Ayres & Sweller (2014) suggest?

### *Semantic-Spatial Displays*

When designing displays to provide text-based feedback, the most intuitive approach may be to centralize the feedback by creating one location displaying feedback pertaining to all aspects of the system. This centralized approach can be a more efficient utilization of available space within the display and users will become accustomed to looking at one location for all text-based feedback. It may also violate the split-attention principle similarly to separable displays by requiring the human to mentally integrate the text with the component of the system to which it pertains (Ayres & Sweller, 2014). An alternative approach is to spatially integrate the text-based feedback within the physical representation of the system, specifically locating the text in close proximity to component(s) of the system to which the feedback pertains.

Semantic-spatial displays present text in spatially organized components typically presented as a node-link diagram with the nodes containing the text and the links representing the conceptual relationships between the nodes (Figure 1) (Butcher, 2014). The spatial location of the nodes also conveys information pertaining to the relationship between them. These displays allow for the proximal integration of text-based information with the system component the feedback pertains to, reducing or eliminating the extraneous load associated when attention must be split between two separate information sources.

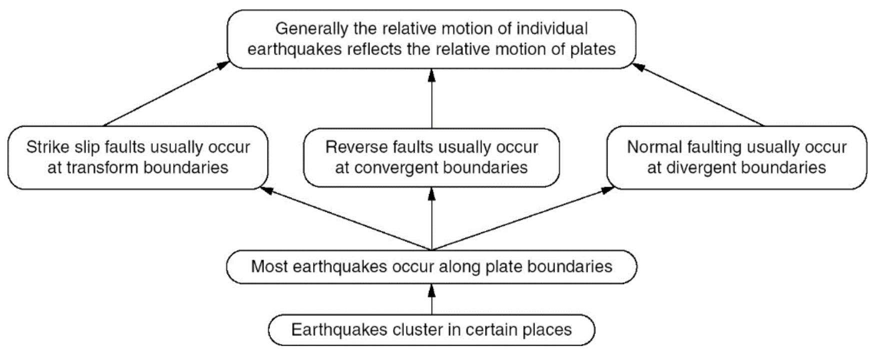


Figure 1. A Concept map is an example of a semantic-spatial display (Butcher, 2014, p. 186)

Research has shown that semantic-spatial displays can improve problem-solving performance and mental model accuracy (Mayer, Dyck, & Cook, 1984). This suggests that the use of semantic-spatial displays may be an effective way to present text based explanatory feedback during interaction with a system, aiding in the development of dynamic mental models representing the behavior of the system. If the node locations correspond to the structure of the system the semantic-spatial explanatory feedback should serve to strengthen both the static mental model associated with the configuration of the system as well as the dynamic mental model associated with the behavior of the system, resulting in a superior functional understanding.

### Measuring Understanding

Determining how variations in display types influence the implicit and explicit understanding of a system requires us to measure each independently. Since implicit and explicit understanding can each contribute to performance it can be difficult to know whether one or both systems is responsible. One method for discerning between them is awareness. Sloman (1996) claims that in the associative system only the result is accessible to consciousness, the process of arriving at that result is not. This aligns with Tulving's (1985) claim that implicit understanding must be expressed directly. The rule-based system allows access to both the process and the result. Therefore, testing implicit understanding should focus on the process and explicit understanding on the result.

Testing understanding is accomplished by measuring the ability to transfer previously presented material to novel situations (Mayer, 2014b). Automation failure events require a human to apply the knowledge and understanding gained under automated conditions to a task that must be performed manually. Therefore, examining the decisions humans make in return-to-manual conditions can be considered a method for measuring the implicit understanding of a system. Measuring a human's explicit understanding can also be accomplished through other behavioral forms, such as asking questions (Berry & Broadbent, 1984; Broadbent et al., 1986; Tulving, 1985). And assessments of participants' explicit understanding can be administered by asking questions that specifically pertain to the relationships between components of the system and between control actions made by the participant and their corresponding effect on the system. After implicit and explicit understanding are assessed independently, it can then be determined how explicit and implicit feedback influences return-to-manual performance.

Designing displays to improve understanding of dynamic systems has been shown to be a complex endeavor. The resulting mental model would ideally utilize both the rule-based and associative systems of reasoning to maximize their collective problem solving capabilities. Explanatory feedback would assist in the development of schemata that represents behavioral interconnectivity of the parts within the system. The user interface would maximize germane cognitive load while minimizing extraneous load, and would be done without the incurrence of a cumulative cognitive load that exceeds the working memory capacity of either the visual or auditory channel. Finally, the display would promote active processing even at higher levels of automation.

It remains to be determined how different feedback formats influence human understanding of a system and how that understanding influences return to manual performance. Answers to the following questions will be sought through this research:

1. Does variation in automation type influence participants' explicit and/or implicit understanding of a dynamic system?

2. Does variation in display type influence participants' explicit and/or implicit understanding of a dynamic system?
3. Is there an interaction between display type and automation type that influences participants' explicit and/or implicit understanding?
4. Does participants' explicit and/or implicit understanding influence return-to-manual performance?

# Method

## Participants

Participants in this study (69 Female, 23 Male, $M_{age}$ = 22.01) were recruited from the Hawaii Pacific University campus via email, posters, and word of mouth. One participant was excluded for a procedural violation and the second due to a technical failure during the session. The participants were between the ages of 18-35 years old and fluent in spoken and written English with normal or corrected-to-normal hearing and vision. Participants with prior experience playing or operating power plant simulations and games were deemed ineligible for participation. All were volunteers and received either a $15 gift card or six SONA credits as partial fulfillment of course requirements.

## Procedure

The experimental sessions (Table 2) began with a paper-based informed consent and screening questionnaire forms. The participants then began a detailed computer-based tutorial on the operation of the nuclear power plant simulator. This tutorial walked through how the control adjustments affected individual subsystems, the operational range of each subsystem, and what happened when the ranges were exceeded. Instruction was provided, explaining how to satisfy the power demand of the city and how performance was measured in terms of how the energy generated translated into monetary reward. The effects of system damage and penalties were also defined.

Following the tutorial, participants were required to initiate and maintain power generation in a simplified nuclear power plant simulation for a period of 15 minutes (Hurlburt, 2016) (see Appendix E). The participants were asked to bring the nuclear plant online and optimize operations to generate the maximum profit without damaging the subsystems. The participants controlled three settings within the system: (1) the reactor core control rods which moderated the level of output from the core, (2) the primary coolant pump which controlled the level of heat within the reactor core and the heat exchanger, and (3) the secondary coolant pump which increased the steam turbine and ultimately the amount of power the plant generates. The operational ranges of each system component were displayed, and the participants were required to maintain a system state that kept the components within these ranges. If the ranges were exceeded, the system became progressively damaged and participants were monetarily penalized for the repair costs of the damaged sub-systems. Consumer demand for electricity periodically fluctuated and the participants were encouraged to meet this demand as efficiently as possible by not over or under producing relative to demand. Under producing resulted in the failure to capture potential revenue while over production resulted in excessive wear on the plant subsystems requiring an increased maintenance fee. Both over and under production were penalized equally, encouraging participants to operate the plant as efficiently as possible. At predetermined periods throughout each simulation round demand levels for electricity changed. At other periods throughout the simulation, participants were prompted to initiate a secondary task inspection process by pressing the spacebar. The longer the delay in pressing the spacebar the higher the maintenance multiplier rose, increasing overall maintenance costs.

Following the first simulated round, participants completed a NASA TLX (Hart & Staveland, 1988) subjective workload assessment (see Appendix A). The simulation was then reset, and participants were asked to initiate and maintain the simulation for a second 15 minute round, under the same conditions and direction. Participants then completed a second NASA TLX followed by an assessment consisting of a series of questions to determine their understanding of how the positive or negative manipulation of the three controls influence each subsystem within the plant and the relationship between subsystems (see Appendix B).

Following the assessment, participants watched a brief video outlining the differences between the first two simulation rounds and the third return-to-manual round. In this portion of the experimental session all participants operated the simulation with reduced automated assistance. This mode provided the lowest level of assistance to the operators and was intended to mimic the manual performance of the task. Following the return-to-manual round, participants completed a third NASA TLX assessment pertaining specifically to their experience in that round.

| Step | Description | Duration (Min) |
|---|---|---|
| 1 | Participant reception & administrative activities | 5 |
| 2 | Detailed tutorial of system | 10 |
| 3 | Simulation Round 1 – Operation of the system with the intent of maximizing performance | 15 |
| 4 | NASA-TLX Assessment 1 | 5 |
| 5 | Simulation Round 2– Operation of the system with the intent of maximizing performance | 15 |
| 6 | NASA-TLX Assessment 2 | 5 |
| 7 | Assessment of participants understanding of the rules that govern the operation of the system (i.e. Explicit Understanding) | 10 |
| 8 | Return-to-Manual Round – Participant operates the simulation under a reduced automation condition | 15 |
| 9 | NASA-TLX Assessment 3 | 5 |
| 10 | Participant debrief | 5 |
| | **Total** | **90** |

Table 2. Experiment session procedural steps and duration

**Stimuli & Experimental Design**

The experiment was a 2x3x3 mixed design, featuring two levels of Automation Type (decision automation, no-decision automation) outlined by the PSW model (Parasuraman et al., 2000), and three levels of Display Type (separable, configural, and semantic-spatial) for a total of six conditions. Each participant performed three Simulation Rounds (repeated measure). Participants were aided by automated support in round 1 and 2, and this support was removed in the third, return-to-manual (RTM) round.

**Display Types**

All display types (separable, configural, and semantic-spatial) consisted of nine subsystems (Figure 2) and three controls (Figure 3). Each subsystem had a numeric digital readout (Figure 4) displaying its current operational status. The maximum operational range was statically displayed next to the subsystem readout to inform the operator of the max readout value allowed before the system started to become damaged. The numeric display changed color to alert the operator that the subsystem state had exceeded its operational limit. When the system was within “normal” operating limits, the text color remained white. When the reading exceeded the operational limit, the text color changed to red indicating the subsystem was being damaged. Each subsystem display also had a linear gauge (Figure 5) that indicated the same warning and damage thresholds, but also graphically indicated the rate of change and proximity to these thresholds. This eliminated the need for the operator to mentally calculate the rate of change and how close the subsystem was to reaching its operational limit.

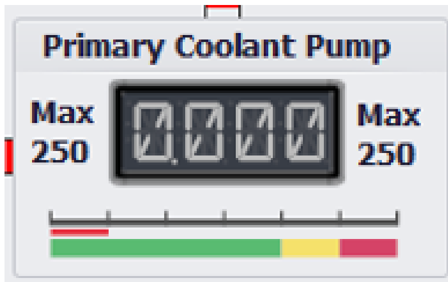


Figure 2. Subsystem Design


Figure 3. Operator Controls

Figure 4. Subsystem Digital Readout (White, Red)

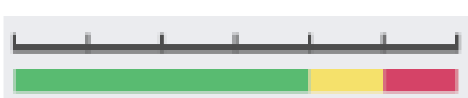

Figure 5. Subsystem Linear Gauge

### *Separable Display*

The separable display featured nine subsystems; each included digital readouts and linear gauges (Figure 6). This display required participants to focus their attention on each subsystem individually to understand how the subsystems were affected by changes to the controls. Comparisons between subsystems were also necessary, requiring the participants to infer the relationships between them.

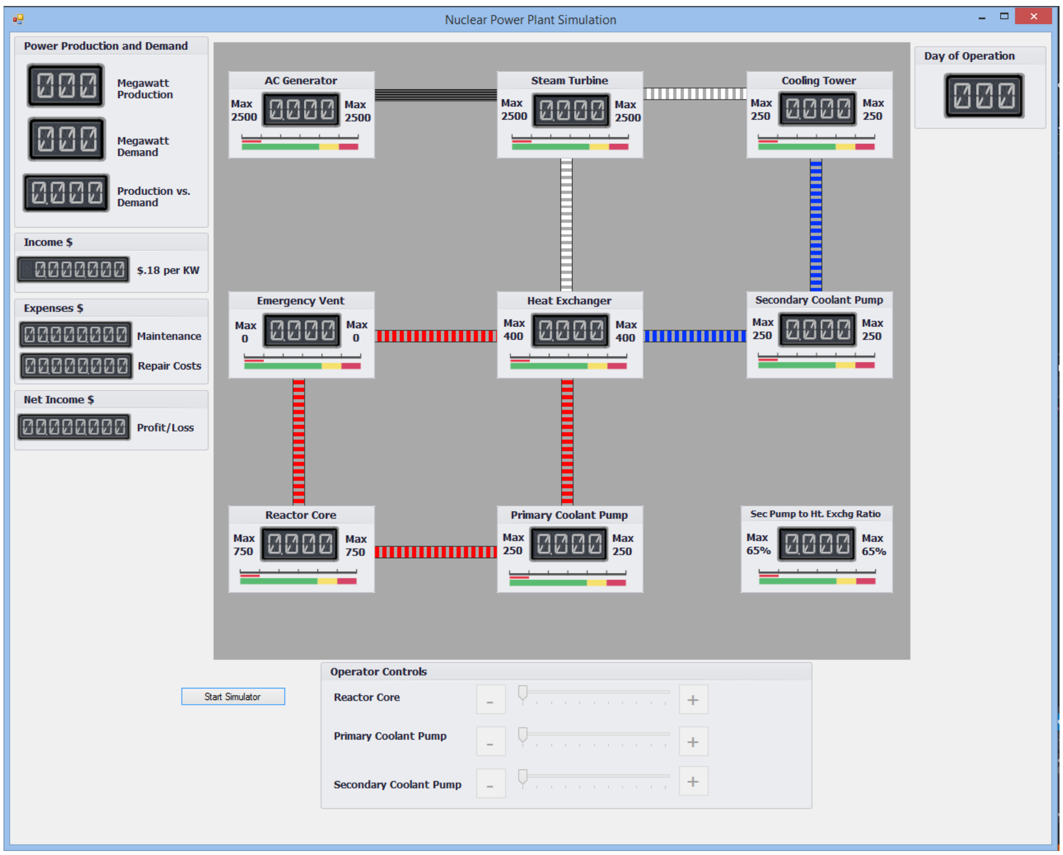


Figure 6. Separable Display Type

### *Configural Display*

The configural display replaced the individual subsystem linear gauges with a single large radar graph for the purpose of displaying the rate of change and the proximity to operational range boundaries (Figure 7). The operational ranges for each subsystem were normalized onto a scale between 0 and 100 for the purpose of simultaneous display on a single radar chart. The configural display type allowed the operator to view the status of all subsystems in a combined visualization. Conceptually, this would allow the operator to more easily identify the relationships between changes made to the controls and the responses of the subsystems, as well as how the subsystem readings moved in relation to one another.

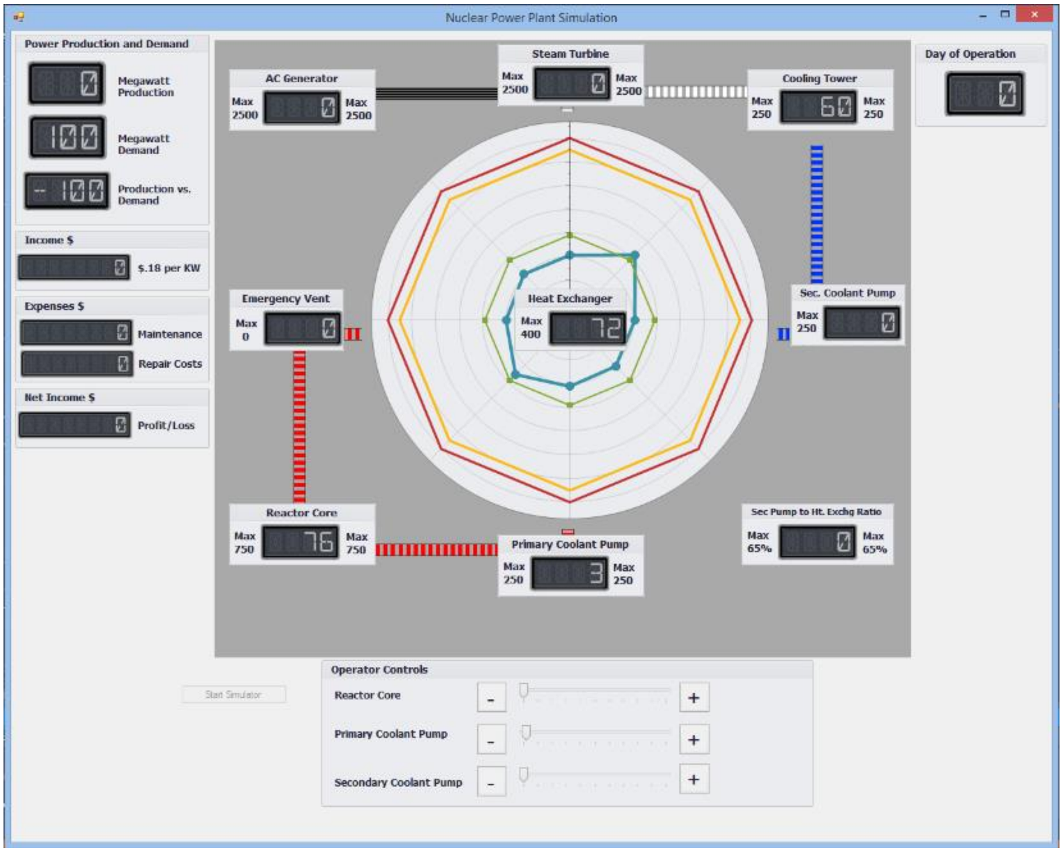


Figure 7. Configural Display Type

### *Semantic-Spatial Display*

The semantic-spatial display utilized the same design as the separable display with the addition of textboxes that provided real time explanatory feedback pertaining to the current state of the system (Figure 8). The display was designed to test if a mental model developed through the simultaneous display of implicit and explicit systems feedback simultaneously improved performance over a mental model that was developed through implicit feedback alone.

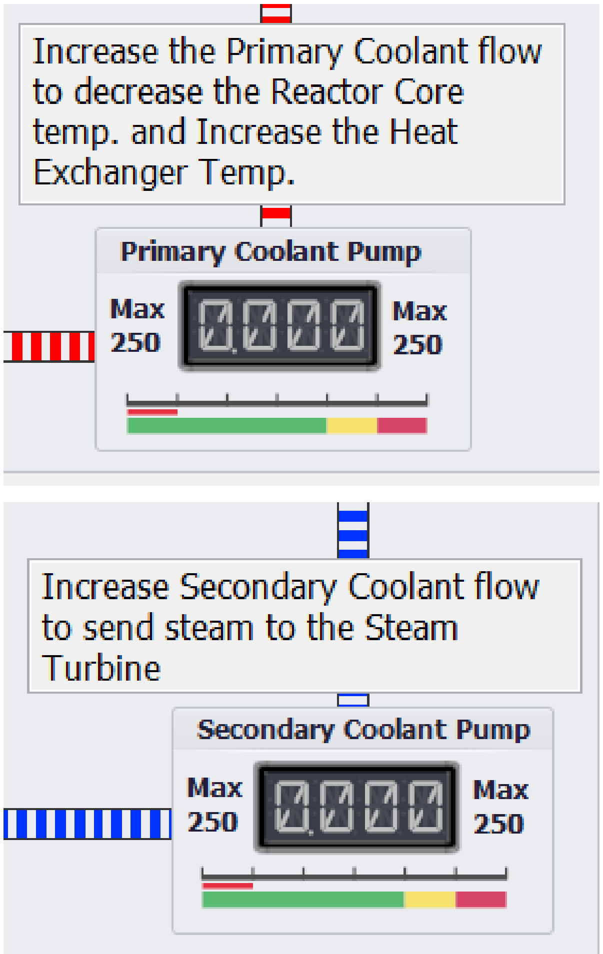


Figure 8. Semantic-spatial Feedback Examples

**Return-to-manual**

The display in the return-to-manual round of the experiment was identical for all conditions. In the return-to-manual round, the linear gauges, radar graph, and semantic-spatial textboxes were removed from the display (Figure 9). The digital readouts no longer changed from white to red when the operational limit of the subsystem was exceeded. These changes required the participant to continuously assess the rate at which the readouts were changing to keep them operating within the defined parameters. Absolute absence of automation was not possible or reasonable due to the complex nature of nuclear power generation, precluding the use of a true manual design.

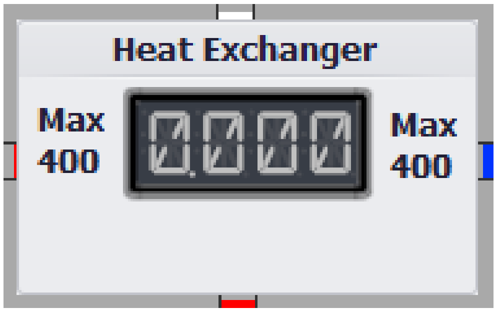

Figure 9. Return-to-Manual Subsystem Design

## Automation Types

The two automation types were defined by the presence or absence of automated decision support. This decision automation was intended to relieve the operator of the decision-making responsibility required to successfully operate the plant.

### *Decision Automation*

The controls used to operate the power plant in the three conditions with decision automation graphically indicated which adjustments needed to be made to bring the plant into an optimal state (Figure 10). Participants were informed that they may follow the directed prompts or supersede their direction.

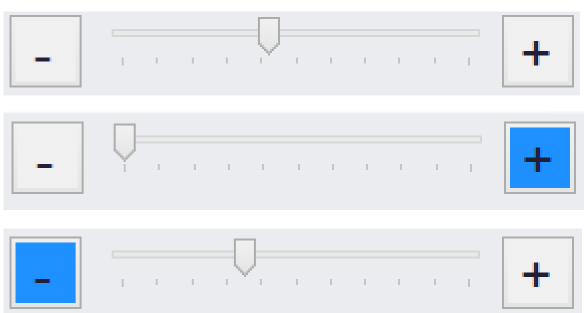

Figure 10. Decision Automation – Control Prompts

### *No-Decision Automation*

Participants did not receive graphical control adjustment recommendations in the three no-decision automation conditions and were required to make all decisions pertaining to control adjustments.

## Dependent Variables

### *Performance*

Performance was assessed through three measurements: Net Income, Production Delta, and Repair Costs.

Net Income assessed participants' overall ability to generate revenue and was calculated based on the amount of power sold (18 cents per kilowatt hour) minus the maintenance cost for producing the power (9 cents per kilowatt hour) and Repair Costs for damaging the system components. Production Delta measured how efficiently the demand for electricity was met and was calculated by averaging the absolute difference between the demand for electricity and the amount produced throughout each simulation round. A lower production delta indicated greater efficiency in meeting demand. Repair costs were assessed to monetarily penalize participants for exceeding the operational limits of the subsystems. A charge of $750 per 8-hour increment ($2250 per day) was charged for each subsystem that exceeded its operational limit. Multiple subsystems could be assessed this fee simultaneously.

### *Workload*

Workload was measured by response times of the secondary task (Sethumadhavan, 2009), and subjective workload was measured through the NASA TLX scores (Hart & Staveland, 1988).

### *Situational Awareness*

Situational Awareness is conventionally measured through direct indicators such as the situation awareness global assessment technique (SAGAT) (Endsley, 1988), but is also measured indirectly by measuring performance consequences that pertain to a lack of information sampling, understanding, or inability to correctly anticipate the behavior of the automation (Onnasch et al., 2014). This study indirectly measured situational awareness by assessing the participant's implicit and explicit understanding of how the nuclear power plant functioned.

### *Implicit Understanding*

Implicit understanding was measured two ways (omission errors, commission error rate) for two different states of the system (demand, damage), resulting in four implicit measures.

Changes made to the three system controls (Reactor Core, Primary Coolant, Secondary Coolant) controls were deemed correct or incorrect by examining their influence on the system. Correct control changes brought the system closer to an optimal state whereas incorrect changes moved the system state away. The state of the system was determined as optimal when the amount of electricity produced exactly met demand, while none of the sub-systems exceeded their operational limit.

The goal of meeting demand was continuous and occurred throughout the entire simulation round, whereas stopping damage to the system was an intermittent goal that was contingent upon previous performance failures that resulted in the system initially entering a damaged state. Assessment of the correctness of decisions was contextualized between these two states. The demand commission error rate represented the accuracy of control changes in relation to meeting demand and was calculated by dividing the number of incorrect control changes by the total number of control changes. Correct control adjustments brought the system closer to meeting demand, incorrect control adjustments did not. The damage commission error rate was measured by dividing the number of incorrect control adjustments by the total number of control adjustments that occur while the system is in a damaged state. Correct control adjustments moved the damaged subsystem(s) closer to the operational limit; incorrect adjustments did not.

The dynamics of the system dictated that the system was meeting, moving towards, or moving away from an optimal state (demand or damage). Allowing the system to move away from an optimal state was considered an omission error. Omission errors measured the total amount of time (in simulated 8-hour increments) that the system moved away from an optimal state, assessing the participants' awareness of the state of the system and their ability to rectify undesired system behavior. Demand omission errors were possible throughout the duration of each simulation round, whereas damage omission errors were only possible while the system while the system was in a damaged state.

These definitions of omission and commission errors vary slightly from those defined by Mosier & Skitka (1996). They are not a result of the automation's failure to identify or direct a system change, but are a result of the operator's failure to do so.

### ***Explicit Understanding***

Measurement of participants' explicit understanding of the rules that regulated the system occurred through an assessment score that was determined by subtracting the total number of incorrect answers from the total number of correct answers (Appendix B) (Broadbent et al., 1986).

## Results

Three-way mixed analyses of variance (ANOVA) were performed to assess the influence of independent variables Automation Type (AT), Display Type (DT), and Simulation Round (repeated measure) on each dependent variable. AT included two levels, Decision Automation (DA) and No-Decision Automation (No-DA) and DT consisted of three levels, Separable (Sep), Configural (Conf), and Semantic-Spatial (SS). Simulation Round consisted of three rounds – the operator was supported by automation in the first two rounds, and this automated support was removed in the third return-to-manual (RTM) round. Additionally, a three-way mixed ANOVA was performed to examine the influence of operating the simulation with automated support during the first two simulation rounds. A one-way ANOVA examining the RTM round was also performed. If statistically significant effects were identified beyond differences in Simulation Rounds in the prior analyses, a two-way mixed ANOVA featuring the Display Type:Automation Type conditions and Simulations Rounds (repeated measure) was also performed to understand how each DT:AT combination influenced dependent variables. The means and standard error for statistically significant results were represented graphically, while the means and standard deviations for all results are represented in tabular format in Appendix C. All pairwise comparisons were subject to Bonferroni adjustments, with reported p-values reflecting this adjustment. An alpha level of .05 was used to indicate significance for all statistical tests.

Stepwise multiple linear regression was calculated to predict the difference between net income, production delta and repair costs in the return-to-manual round and those achieved in Simulation Round 2. This difference measured the impact of the removal of automated support and was calculated by subtracting round 2 performance scores from those achieved in the RTM round. The difference was referred to as the "RTM Delta". Workload and understanding measurements from Simulation Rounds 1 and 2 were used as predictor variables to determine their relationship with RTM Delta. Calculations were performed for the total study population, and for each Automation Type and Display Type level to determine if variations in treatments influenced the RTM Delta differently. Descriptive statistics are represented in Appendix D.

## Primary Task Performance Measurements

### *Net Income*

The results of a three-way mixed analysis of variance (ANOVA) examining the influence of Automation Type, Display Type, and Simulation Round (repeated measure) on participant net income earnings revealed statistically significant main effects for Automation Type, $F(1,84) = 14.06$, $p < .001$, $\eta_p^2 = .143$, and Simulation Round $F(1.79,149.90) = 19.79$, $p < .001$, $\eta_p^2 = .191$ (reported with Greenhouse-Geisser correction). The main effect for Display Type failed to reach statistical significance, $F(2,84) = 2.47$, $p = .091$, $\eta_p^2 = .056$. In addition, there was a statistically significant interaction between Automation Type x Simulation Round, $F(1.79,149.90) = 15.18$, $p < .001$, $\eta_p^2 = .153$ (reported with Greenhouse-Geisser correction). All other interaction effects failed to reach statistical significance. A second three-way ANOVA analyzing differences in net income while automated support was available in Simulation Rounds 1 & 2 identified a significant main effect for Automation Type, $F(1,84) = 23.54$, $p < .001$, $\eta_p^2 = .219$. The main effect for Display Type again failed to reach statistical significance, $F(2,84) = 2.48$, $p = .090$, $\eta_p^2 = .056$. Means and standard deviations are provided in Appendix C.

Investigation into the significant main effect for Simulation Round found in the three-way mixed ANOVA revealed a training effect between rounds. Post-hoc tests identified differences in net income between Simulation Rounds 1 and 2, $t(84) = -7.08$, $p < .001$, and round 1 and 3, $t(84) = -3.45$, $p = .003$ (Figure 11). The improvements in performance achieved in round 2 carried forward into the RTM round, suggesting that continued practice operating the system influenced performance to a greater degree than the reduction of automated assistance.

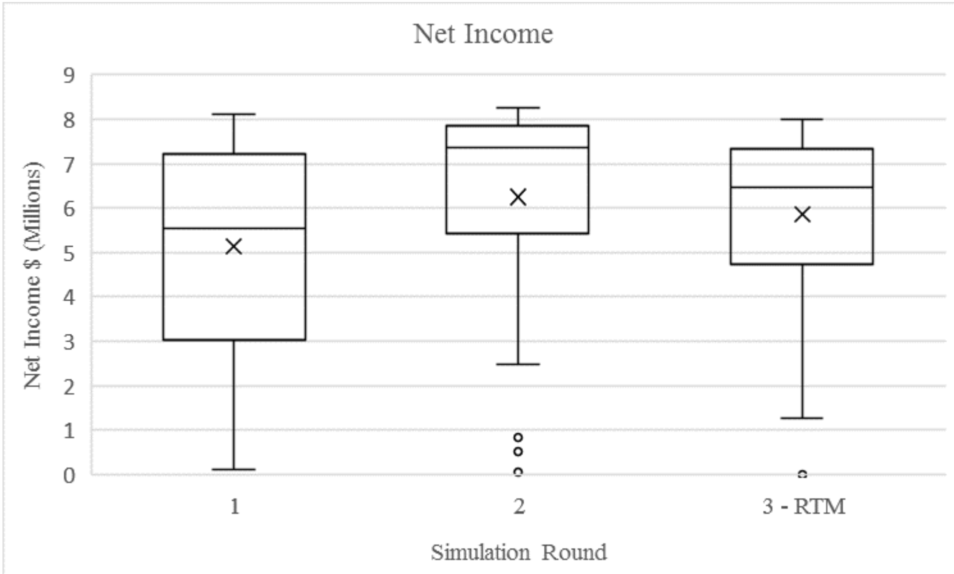


Figure 10. Net Income as a function of Simulation Round

The basis for the significant AT x Simulation Round interaction and AT main effect found in the 3-way mixed ANOVA can be determined by examining Figure 12. As expected, post-hoc contrasts found that net income for the DA group was significantly higher in round 1 than the No-DA group, indicating that decision automation provided an immediate boost in performance, $t(84) = 4.86$, $p < .001$. The DA, $t(84) = -4.47$, $p < .0001$, and No-DA groups, $t(84) = -5.54$, $p < .001$, improved significantly from round 1 to round 2, demonstrating a general ability to improve performance regardless of Automation Type. The improvement in performance afforded by decision automation continued in round 2, as net income was again higher for the DA group, $t(84) = 4.18$, $p = .001$. This improvement appeared to be contingent upon the availability of automated decision support as net income decreased significantly for the DA group in the RTM round, $t(84) = 4.96$, $p < .001$. The No-DA group maintained a significant improvement from round 1 to round 3, indicating that the reduction in automated assistance in the RTM round was less impactful than it was for the DA group, $t(84) = -5.53$, $p < .001$.

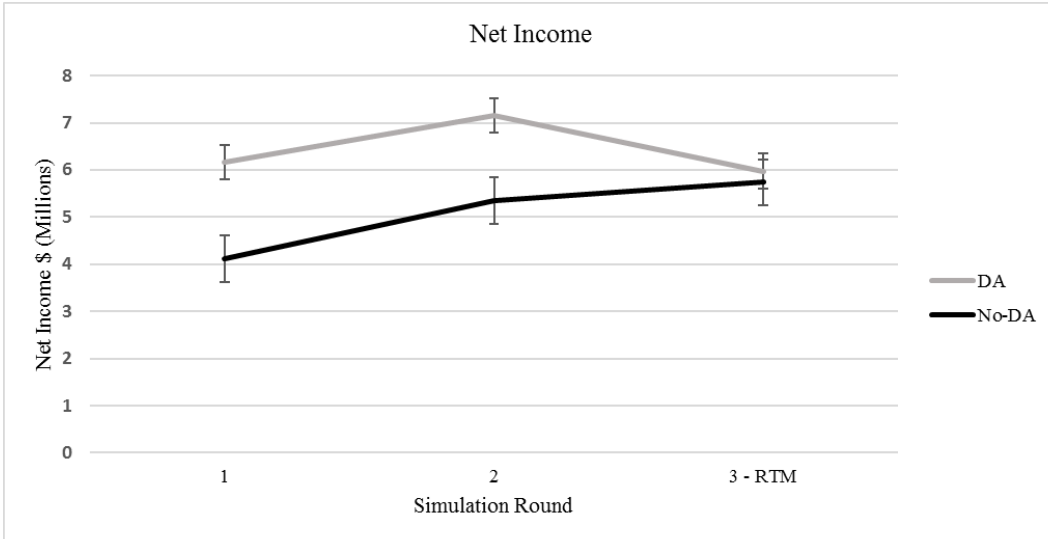


Figure 11. Net Income as a function of Automation Type and Simulation Round

The non-significant trending between Display Types found in the three-way mixed ANOVA can be observed in Figure 13.

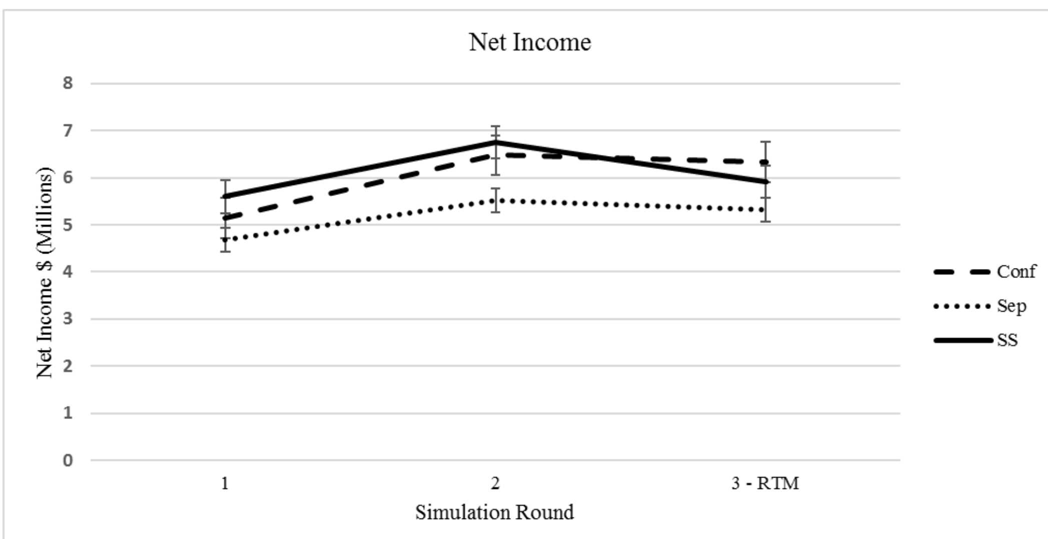


Figure 12. Net Income as a function of Display Type and Simulation Round

To further understand the influence individual Display Type, Automation Type, and Simulation Rounds have on net income, a two-way mixed ANOVA was performed featuring Display Type:Automation Type conditions and Simulations Rounds. Significant main effects were found for Condition $F(5,84) = 4.16$, $p = .002$, $\eta_p^2 = .198$, and Simulation Round, $F(1.79,149.90) = 19.77$, $p < .001$, $\eta_p^2 = .191$, as well as a significant Condition x Simulation

Round interaction $F(8.92, 149.90) = 4.47$, $p < .001$, $\eta_p^2 = .210$. An additional two-way mixed ANOVA examining the operation of the simulation with automated support in simulation rounds 1 & 2, also identified a significant main effect for Condition, $F(5,84) = 6.33$, $p < .001$, $\eta_p^2 = .274$.

Post-hoc contrasts featuring all three simulation rounds found a significant difference between Sep:No-DA and the Conf:DA condition, $t(84) = 3.96$, $p = .002$, and also between the Sep:No-DA and SS:DA conditions, $t(84) = -3.5$, $p = .011$. Differences between the Sep:No-DA and Sep:DA condition nearly reached statistical significance, $t(84) = 3.00$, $p = .054$ (Figure 14).

Post-hoc contrasts investigating the significant main effect for Condition within the ANOVA examining simulation rounds 1 & 2, identified differences between the Sep:No-DA condition and all three DA conditions, as well as differences between the Conf:DA and Conf:No-DA conditions (Table 3).

| Condition (I) | Condition (J) | Mean Difference (I-J) | Std. Error | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|
| Conf:No-DA | Conf:DA | -2369332.00* | 689570.022 | 0.014 | -4452840.63 | -285823.37 |
| Sep:No-DA | Conf:DA | -3135994.00* | 689570.022 | 0.000 | -5219502.63 | -1052485.37 |
| | Sep:DA | -2490241.00* | 689570.022 | 0.008 | -4573749.63 | -406732.37 |
| | SS:DA | -2778843.00* | 689570.022 | 0.002 | -4862351.63 | -695334.37 |

Table 3. Net Income - Statistically significant pairwise comparisons of Display Type:Decision Automation conditions (Simulation Rounds 1 & 2)

These results suggest that there was a clear difference in performance when operating the simulation with automated support (Simulation Rounds 1 & 2), the separable display, and without decision support, than there was when operating with decision support regardless of display type. The results also indicated that decision automation improved performance for operators using the configural display, but the improvement did not carry forward into the RTM round.

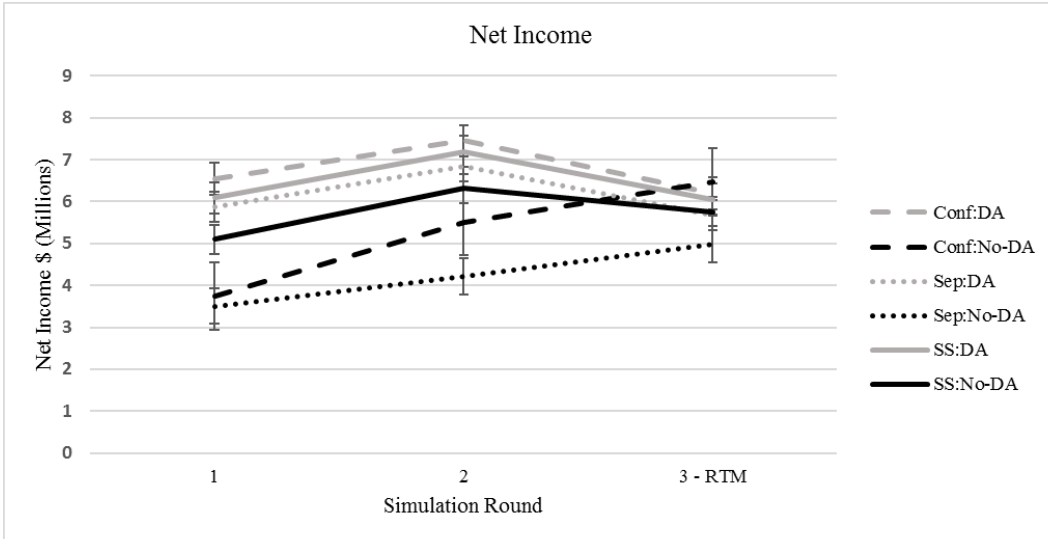


Figure 13. Net Income as a function of Display Type:Decision Automation conditions and Simulation Round

Further investigation of the Condition x Simulation Round interaction found a significant improvement in net income for four of the six conditions from round 1 to round 2 (Conf:No-DA [$t(84) = -4.59$, $p < .001$], Sep:DA [$t(84) = -2.53$, $p = .040$], SS:DA [$t(84) = -3.5$, $p = .016$], SS:No-DA [$t(84) = -3.12$, $p = .007$]), providing additional insight into the findings pertaining to round 2 performance improvements. Net income significantly decreased for all three DA conditions in the RTM round (Conf:DA [$t(84) = 3.04$, $p = .010$], Sep:DA [$t(84) = 2.81$, $p = .019$], SS:DA [$t(84) = 2.75$, $p < .022$]), while the Sep:No-DA, $t(84) = -2.91$, $p = .014$, and Conf:No-DA, $t(84) = -5.37$, $p < .001$, groups improved significantly from round 1 to the RTM round, demonstrating the negative influence decision automation had on RTM performance.

### *Production Delta*

The three-way mixed ANOVA examining the independent variables' influence on production delta revealed statistically significant main effects for factors Automation Type, $F(1,84) = 12.25$, $p = .001$. $\eta_p^2 = .127$, Simulation Round $F(2,168) = 25.15$, $p < .001$, $\eta_p^2 = .230$, and a statistically significant interaction between Automation Type x Simulation Round, $F(2,168) = 11.36$, $p < .001$, $\eta_p^2 = .119$. The main effect for Display Type nearly reached significance, $F(2,84) = 2.89$, $p = .061$, $\eta_p^2 = .064$. An additional three-way mixed ANOVA examining production delta while operating the simulation with automated support in simulation rounds 1 & 2, identified significant main effects for Automation Type, $F(1,84) = 19.92$, $p < .001$, $\eta_p^2 = .192$, and Display Type, $F(2,84) = 3.13$, $p = .049$, $\eta_p^2 = .069$.

A post-hoc analysis of the significant main effect for Simulation Round indicated a training effect, with a significant difference in production delta between simulation rounds 1 and 2, $t(84) = 6.90$, $p < .001$, and round 1 and 3, $t(84) = 5.22$, $p < .001$ (Figure 15). Similar to net income, the improvements in performance found in round 2 carried forward into the RTM round.

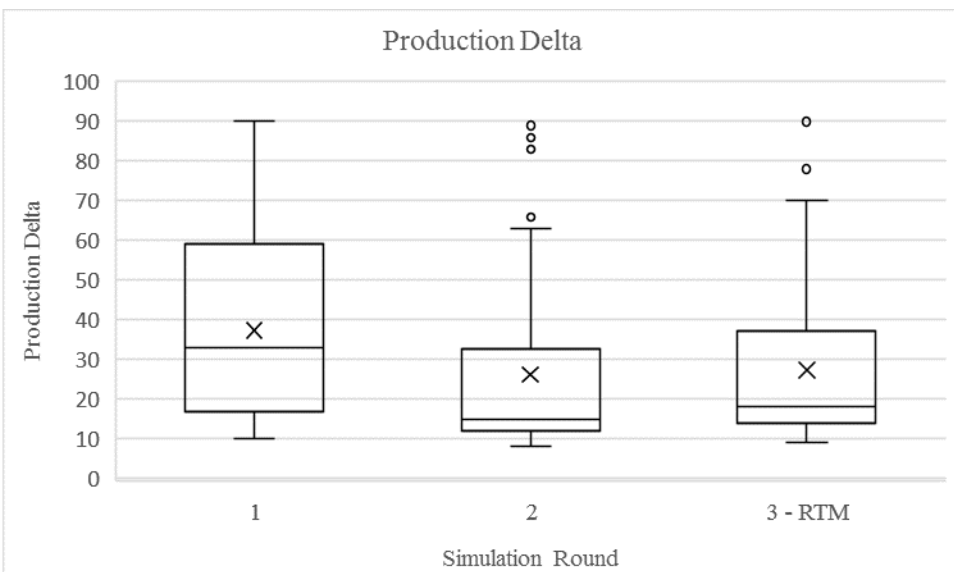


Figure 14. Production Delta as a function of Simulation Round

The source of the significant AT x Simulation Round interaction and AT factor main effect can be found in Figure 16. The delta between energy production and demand is the largest contributing factor to revenue generation within the simulation, explaining the similarity in results between production delta and net income. Post-hoc contrasts found the production delta was significantly lower for the DA group than the No-DA group in round 1, $t(84) = -4.46$, $p < .001$. The DA, $t(84) = 4.365$, $p < .001$, and No-DA groups, $t(84) = 5.38$, $p < .001$, improved significantly from round 1 to round 2, demonstrating an ability to improve regardless of Automation Type. The production delta for the DA group was again lower in round 2 than the No-DA group, indicating that decision automation continued to bolster performance, $t(84) = -3.82$, $p < .001$. Similarly to net income, DA group performance significantly decreased in the RTM round, $t(84) = -3.27$, $p < .001$, while the No-DA group improved from round 1 to round 3, $t(84) = 6.5$, $p < .001$.

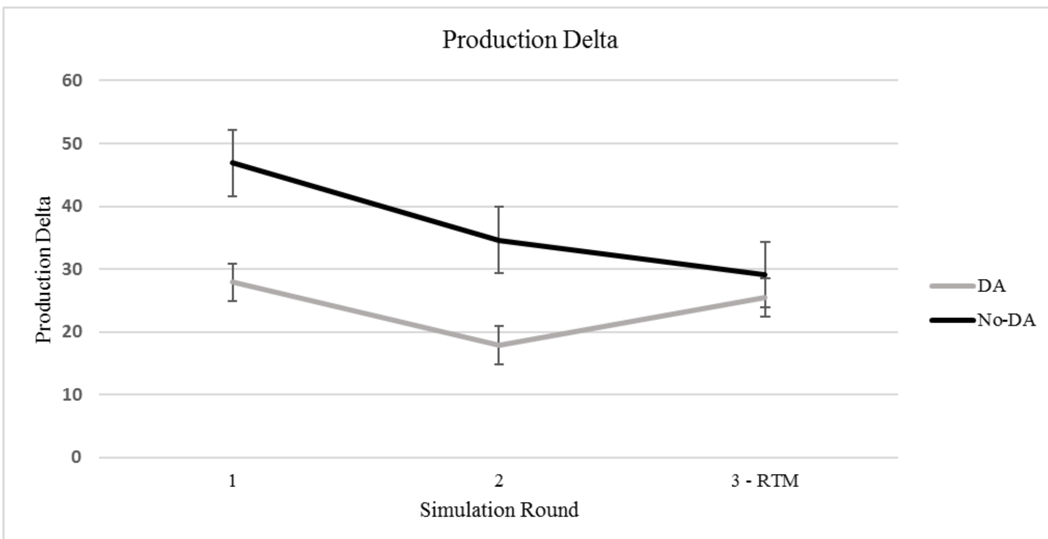


Figure 15. Production Delta as a function of Automation Type and Simulation Round

Post-hoc analysis of the significant main effect for display type when operating the simulation with automated support in rounds 1 and 2 identified a significant difference between the separable and semantic-spatial displays, $t(84) = 2.49$, $p = .045$ (Figure 17). Further analysis identified the difference between these displays was only significant in round 2, $t(84) = 2.60$, $p = .033$.

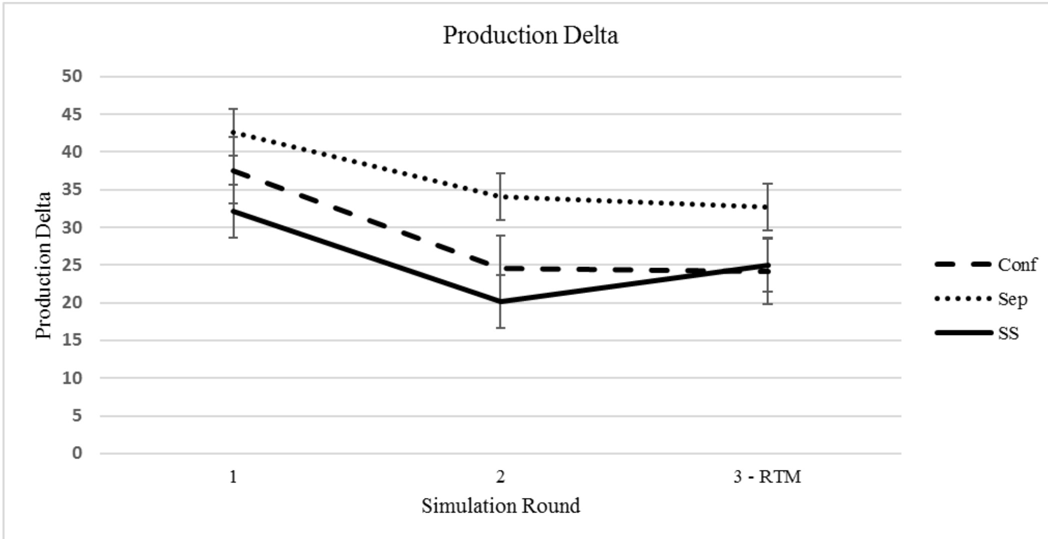


Figure 16. Production Delta as a function of Display Type and Simulation Round

A two-way mixed ANOVA featuring Display Type:Automation Type conditions and all three Simulations Rounds, found significant main effects for Condition, $F(5,84) = 4.06$, $p = .002$, $\eta_p^2 = .195$, and Simulation Round, $F(2,168) = 25.15$, $p < .001$, $\eta_p^2 = .230$, as well as the Condition x Simulation Round interaction, $F(10,168) = 3.51$, $p < .001$, $\eta_p^2 = .173$. A second two-way mixed ANOVA featuring simulation rounds 1 & 2 also identified a significant difference between conditions, $F(5,84) = 5.94$, $p < .001$, $\eta_p^2 = .261$.

Post-hoc contrasts featuring all three simulation rounds identified significant differences were found between the Sep:No-DA and Conf:DA conditions, $t(84) = -3.78$, $p = .004$, and the Sep:No-DA and SS:DA conditions, $t(84) = 3.59$, $p = .009$. Similarly to net income, the differences between the Sep:No-DA and SS:No-DA condition nearly reached statistical significance, $t(84) = -2.95$, $p = .056$.

Post-hoc analyses investigating the significant main effect for Condition identified similar results to those found when examining net income (Figure 18). Pairwise comparisons examining simulation rounds 1 & 2, identified differences between the Sep:No-DA condition and all three DA conditions, as well as differences between the Conf:DA and Conf:No-DA conditions (Table 4).

| Condition (I) | Condition (J) | Mean Difference (I-J) | Std. Error | Sig. | 95% Confidence Interval Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|
| Conf:DA | Conf:No-DA | -22.27* | 6.930 | 0.028 | -43.21 | -1.33 |
| Sep:No-DA | Conf:DA | 30.40* | 6.930 | 0.000 | 9.46 | 51.34 |
| | Sep:DA | 24.00* | 6.930 | 0.013 | 3.06 | 44.94 |
| | SS:DA | 27.83* | 6.930 | 0.002 | 6.89 | 48.77 |

Table 4. Production Delta - Statistically significant pairwise comparisons of Display Type:Decision Automation conditions (Simulation Rounds 1 & 2)

Investigation of the Condition x Simulation Round interaction found a significant improvement in production delta from round 1 to round 2 for three conditions: Conf:No-DA, $t(84) = 4.35$, $p < .001$, SS:DA, $t(84) = 2.92$, $p = .013$, and SS:No-DA, $t(84) = 3.11$, $p = .008$ (Figure 4-8). The Conf:No-DA condition significantly improved production delta again in the RTM round, demonstrating a continued training effect supported by the configural display, $t(84) = 2.54$, $p = .039$. The Sep:No-DA condition exhibited a weaker training effect, improving from round 1 to round 3, $t(84) = 3.43$, $p = .003$.

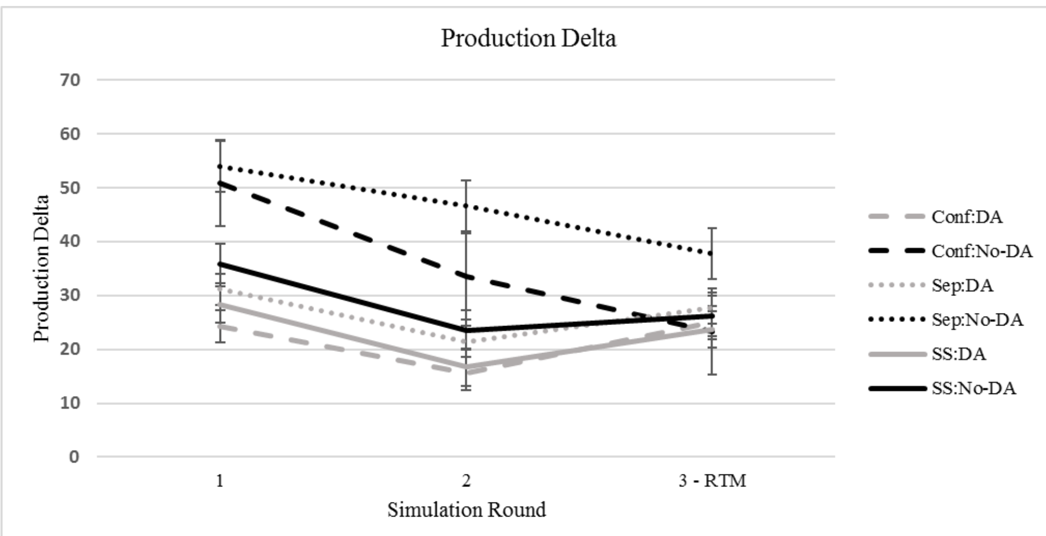


Figure 17. Production Delta as a function of Display Type:Decision Automation conditions and Simulation Round

### ***Repair Costs***

A three-way mixed ANOVA examining repair costs identified statistically significant effects for Simulation Round, $F(1.52,127.43) = 16.54$, $p < .001$, $\eta_p^2 = .164$, and the Automation Type x Simulation Round interaction, $F(1.52, 127.43) = 4.23$, $p = .026$, $\eta_p^2 = .048$ (both reported with Greenhouse-Geisser corrections).

A post-hoc analysis of the significant main effect for Simulation Rounds indicated a significant difference between simulation rounds 1 and 3, $t(84) = -4.64$, $p < .001$, and round 2 and 3, $t(84) = -4.22$, $p < .001$ (Figure 19). The absence of improvement from round 1 to 2 suggests a possible floor effect, or that the additional experience was simply insufficient to facilitate improvement.

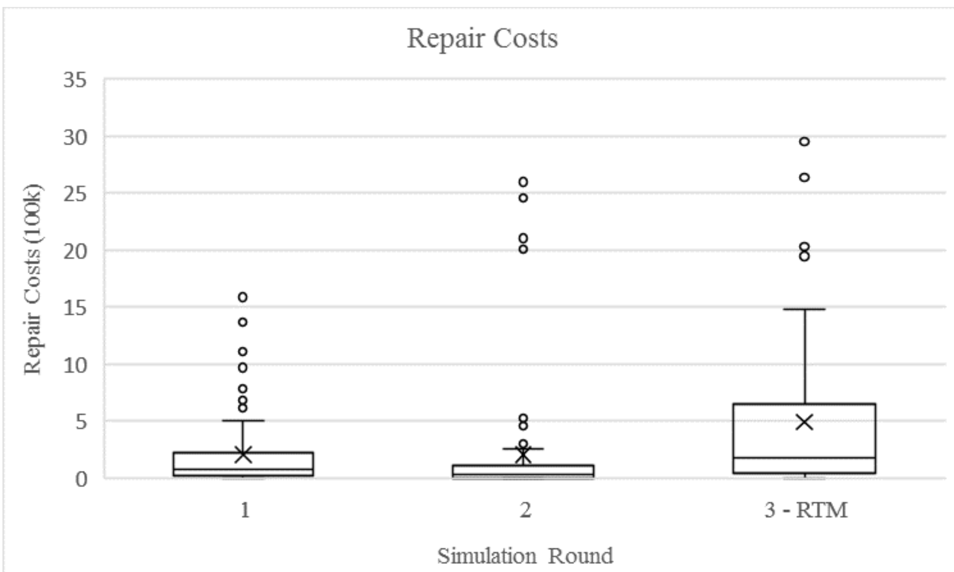


Figure 18. Repair costs as a function of Simulation Round

The AT x Simulation interaction can be identified through the examination of Figure 20. Repair costs for the DA group increased significantly in the RTM round, indicating the comparatively greater impact the reduction in automation had over the No-DA group, $t(84) = -4.5$, $p < .001$.

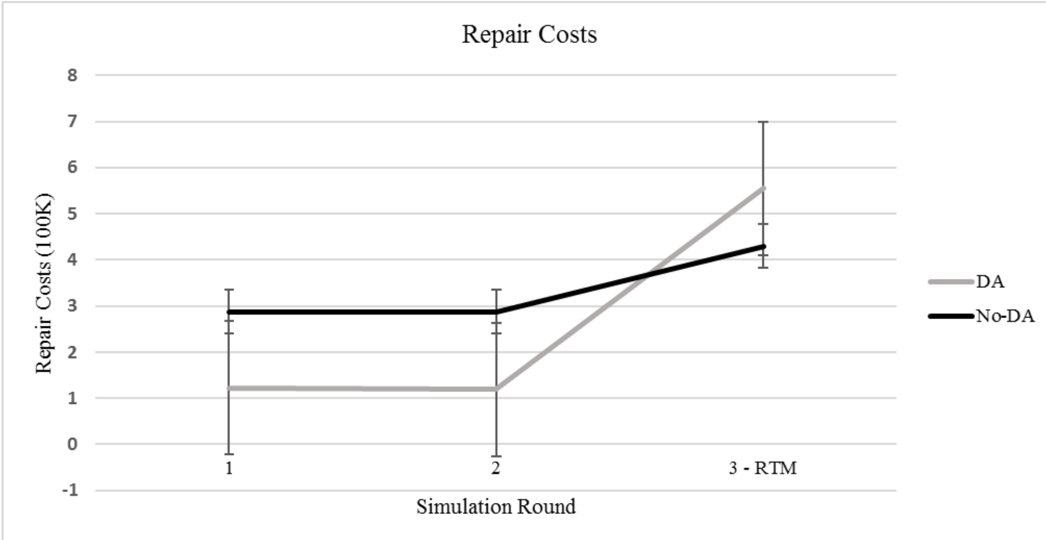


Figure 19. Repair Costs as a function of Automation Type and Simulation Round

A two-way mixed ANOVA featuring the Conditions and Simulation Rounds did not reveal any additional findings.

## Understanding Measurements

### *Demand Omission Errors*

Analysis of demand omission errors revealed statistically significant main effects for Automation Type $F(1,84) = 13.41$, $p < .001$, $\eta_p^2 = .138$, and Simulation Round $F(1.49, 124.76) = 14.22$, $p < .001$, $\eta_p^2 = .145$ (reported with Greenhouse-Geisser correction), and a significant interaction between Automation Type x Simulation Round $F(1.49, 124.76) = 10.27$, $p < .001$, $\eta_p^2 = .199$ (reported with Greenhouse-Geisser correction). A second three-way mixed ANOVA examining simulation rounds 1 & 2, identified a significant main effect for Automation Type, $F(1,84) = 25.839$, $p < .001$, $\eta_p^2 = .235$.

A post-hoc analysis examining the significant main effect for simulation rounds indicated a significant improvement between simulation rounds 1 and 2, $t(84) = 6.95$, $p < .001$. The analysis also indicated that there was a significant decline in performance in the RTM round when compared to round 2, suggesting that the difficulty of operating the simulation under reduced automation outweighed any continuation of the training effect experienced in round 2, $t(84) = -4.08$, $p = .001$ (Figure 21).

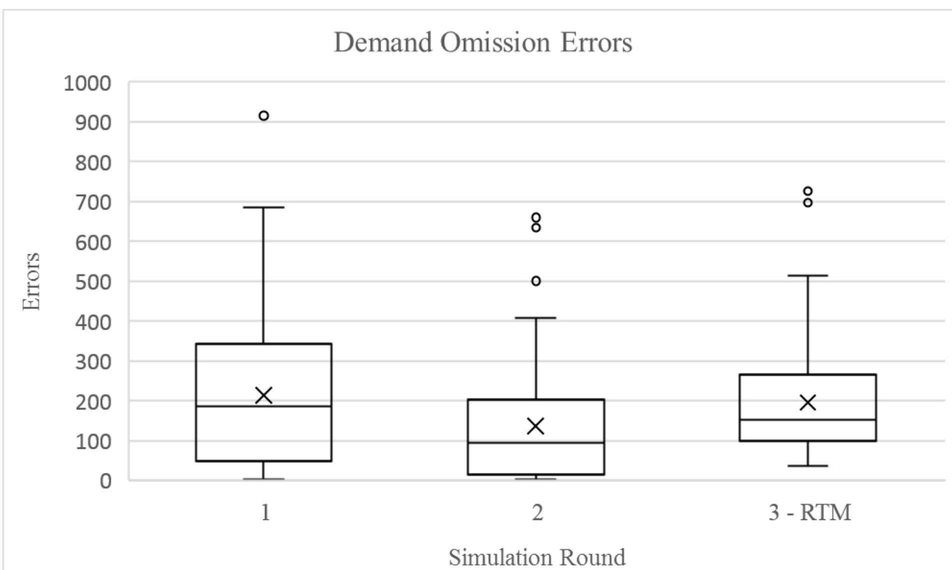


Figure 20. Demand Omission Errors as a function of Simulation Round

The origins of the significant AT main effect and the AT x Simulation round can be identified in Figure 22. Like net income and production delta, the presence of automated decision support improved participants' ability to reduce demand omission errors. No-DA demand omission errors were significantly higher than DA errors in both round 1, $t(84) = -5.00$, $p < .001$, and round 2, $t(84) = -4.48$, $p < .001$. Both the DA group, $t(84) = 3.51$, $p = .002$, and the No-DA group, $t(84) = 6.33$, $p < .001$, improved from round 1 to round 2, with the No-DA group also exhibiting a training effect from round 1 to 3, $t(84) = 4.18$, $p < .001$. The DA group's performance decreased significantly in the RTM round, $t(84) = -6.37$, $p < .001$, indicating the reduction of automated support again appeared to negatively impact the DA group to a greater extent than the No-DA group.

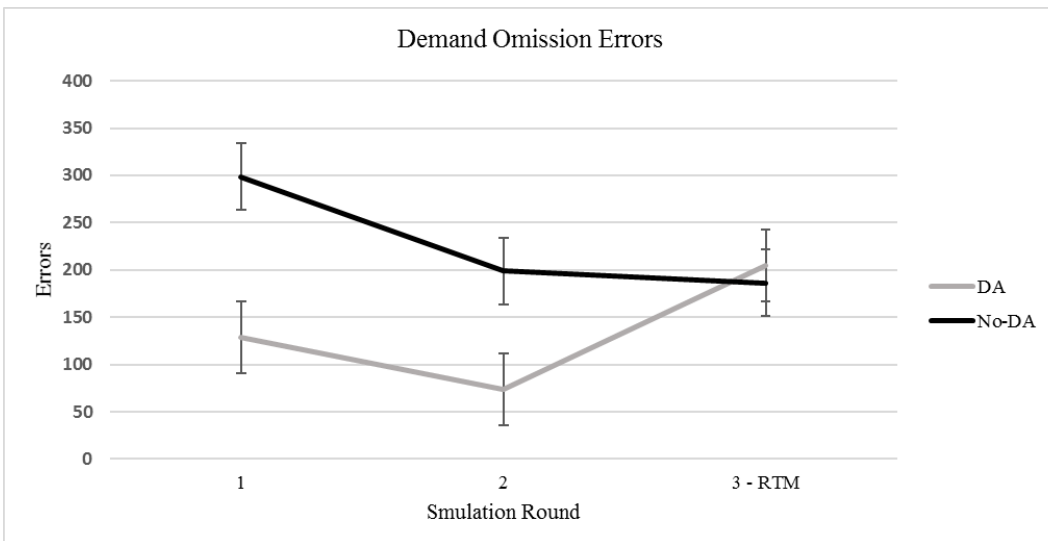


Figure 21. Demand Omission Errors as a function of Automation Type and Simulation Round

The Condition x Simulation Round two-way mixed ANOVA found significant main effects for Condition, $F(5, 84) = 3.95$, $p = .003$, $\eta_p^2 = .189$, and Simulation Rounds, $F(1.49, 124.76) = 14.22$, $p < .001$, $\eta_p^2 = .145$, as well as a significant effect for the Condition x Simulation Round interaction, $F(7.43, 124.76) = 5.66$, $p < .001$, $\eta_p^2 = .252$ (Simulation Round and the interaction were reported with Greenhouse-Geisser correction). A second two-way mixed ANOVA featuring simulation rounds 1 & 2 also identified a significant difference between conditions, $F(5,84) = 7.03$, $p < .001$, $\eta_p^2 = .295$.

Post-hoc contrasts investigating the significant main effect for Condition within the ANOVA examining simulation rounds 1 & 2, identified differences between the Sep:No-DA condition and all three DA conditions, as well as differences between the Conf:DA condition and all three conditions (Table 5).

| Condition (I) | Condition (J) | Mean Difference (I-J) | Std. Error | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|
| Conf:No-DA | Conf:DA | 197.70* | 50.251 | 0.003 | 45.87 | 349.53 |
| | Sep:DA | 158.23* | 50.251 | 0.034 | 6.40 | 310.07 |
| | SS:DA | 187.07* | 50.251 | 0.005 | 35.23 | 338.90 |
| Sep:No-DA | Conf:DA | 215.33* | 50.251 | 0.001 | 63.50 | 367.17 |
| | Sep:DA | 175.87* | 50.251 | 0.011 | 24.03 | 327.70 |
| | SS:DA | 204.70* | 50.251 | 0.002 | 52.87 | 356.53 |

Table 5. Demand Omission Errors - Statistically significant pairwise comparisons of Display Type:Decision Automation conditions (Simulation Rounds 1 & 2)

A post-hoc analysis of the significant main effect for Condition examining all three simulation rounds found that the Sep:No-DA condition had significantly higher demand omission errors than both the Conf:DA, $t(84) = -3.5$, $p = .010$, and the SS:DA conditions, $t(84) = -3.31$, $p = .021$ (Figure 23). These results were similar to the findings for net income and production delta, demonstrating the tight coupling between profitability, efficiency, and allowance of the production of electricity to deviate from demand.

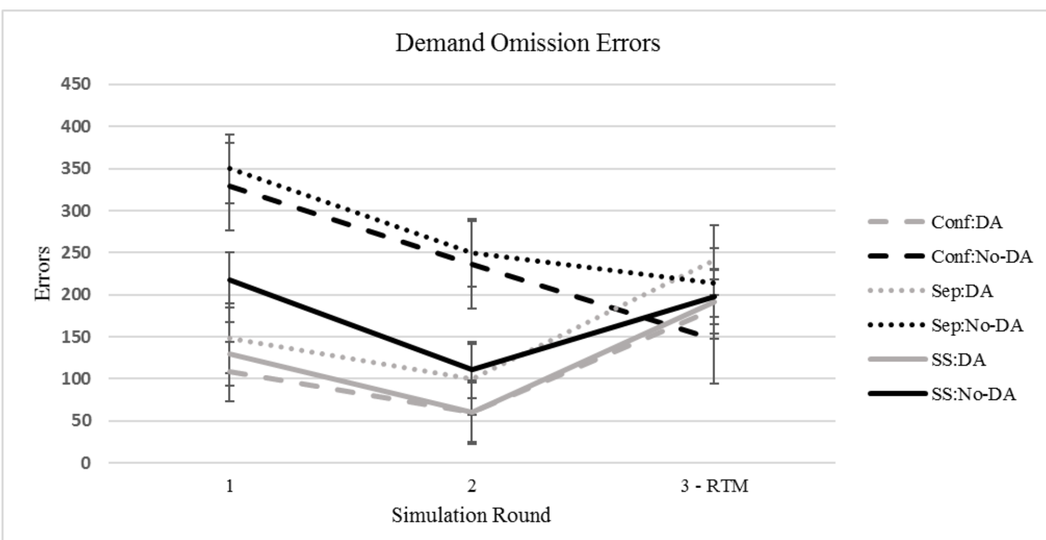


Figure 22. Demand Omission Errors as a function of Display Type:Decision Automation conditions and Simulation Round

Investigation into the Condition x Simulation Round interaction found a training effect for demand omission errors from round 1 to round 2 for four of the six conditions (Conf:No-DA [$t(84) = 3.40$, $p = .0207$], Sep:No-DA [$t(84) = 3.65$, $p = .001$], SS:DA [$t(84) = 2.52$, $p = .041$], SS:No-DA [$t(84) = 3.91$, $p = .001$]), providing insight into the improvements found in round 2. Demand omission errors increased significantly in the RTM round for all three DA conditions (Conf:DA [$t(84) = -3.42$, $p = .003$], Sep:DA [$t(84) = -3.96$, $p < .001$], SS:DA [$t(84) = -3.65$, $p = .001$]), while decreasing for the Conf:No-DA condition, $t(84) = 2.48$, $p = .046$ . The Conf:No-DA, $t(84) = 3.91$, $p = .001$, and the Sep:No-DA, $t(84) = 2.91$, $p = .014$, also exhibited a training effect throughout, significantly improving from round 1 to round 3.

***Demand Commission Error Rate***

The three-way mixed ANOVA examining demand commission error rates revealed statistically significant main effects for: Automation Type ($F$(1,84) = 11.01, $p$ = .001, $\eta_p^2$ = .116), Simulation Round ($F$(1.75,147.22) = 7.12, $p$ = 0.002, $\eta_p^2$ = .078), and a significant interaction between Automation Type x Simulation Round ($F$(1.75,147.22) = 18.01, p < 0.001, $\eta_p^2$ = .177) (reported with Greenhouse-Geisser corrections). The effect for the interaction between Display Type x Simulation Round, nearly reached statistical significance, $F$(3.51,147.22) = 2.50, p = 0.053, $\eta_p^2$ = .056. A second three-way mixed ANOVA examining simulation rounds 1 & 2, identified significant a main effect for Automation Type, $F$(1,84) = 29.50, $p$ < .001, $\eta_p^2$ = .260, and the main effect for Display Type nearly reached significance, $F$(2,84) = 3.05, $p$ = .052, $\eta_p^2$ = .068.

A post-hoc analysis examining the significant main effect for Simulation Round identified a significant difference in demand commission error rates between simulation rounds 1 and 2, indicating that participants were collectively able to improve with practice, $t$(84) = 3.46, $p$ = 0.003. Error rates increased from round 2 to round 3, providing evidence that operating under reduced automation negatively impacted participants' ability to make correct demand related control adjustments, $t$(84) = -3.71, $p$ = .001 (Figure 24).

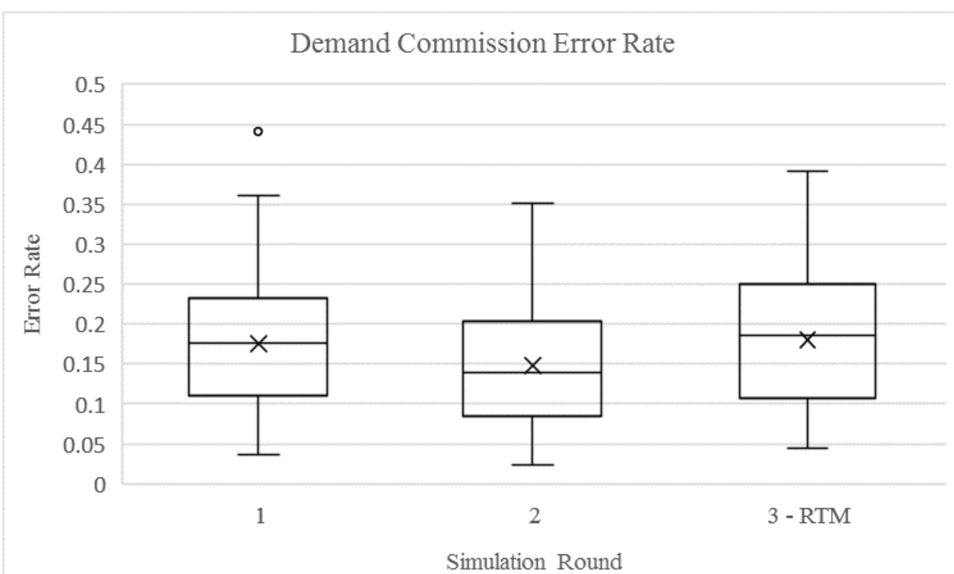


Figure 23. Demand Omission Error Rate as a function of Simulation Round

The basis for the significant AT x Simulation Round interaction and AT main effect found in the 3-way mixed ANOVA can be determined by examining Figure 25  Demand commission error rates were lower for the DA group in round 1, $t(84) = -6.81$, $p < .001$, and round 2, $t(84) = -2.44$, $p < .017$, indicating an improvement in the rate of correct demand related control changes when decision automation was available.  The No-DA group exhibited a training effect, improving from round 1 to round 2, $t(84) = 4.96$, $p < .001$, while the DA group error rate remained relatively unchanged.  Similar to other findings, demand commission error rates increased significantly in the RTM round for the DA group, $t(84) = 4.82$, $p < .001$.

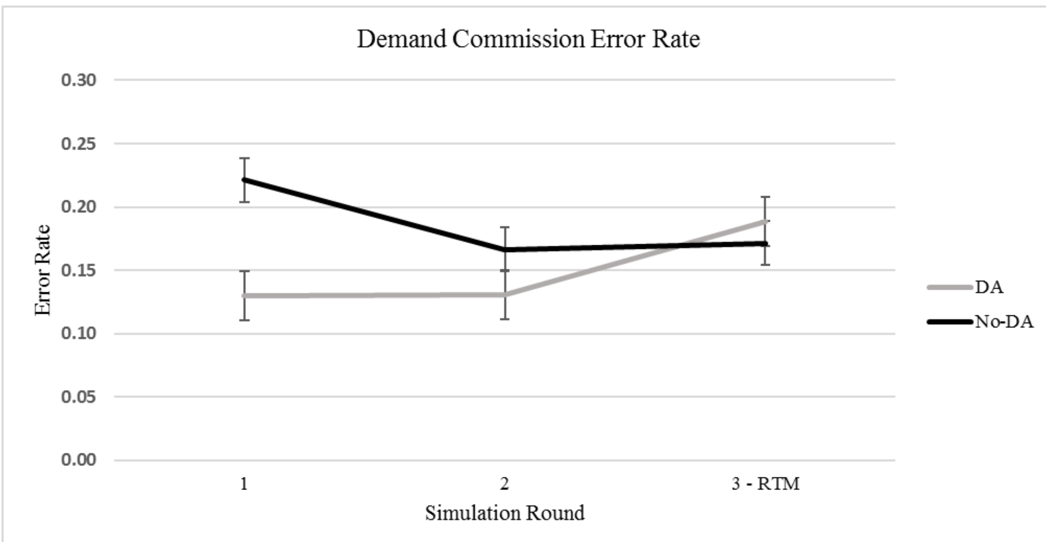


Figure 24.  Demand Commission Error Rate as a function of Automation Type and Simulation Round

The nearly-significant trending of the Display Types x Simulation Round interaction found in the three-way mixed ANOVA, and the nearly-significant main effect for Display type found when examining rounds 1 and 2 can be observed in Figure 26.

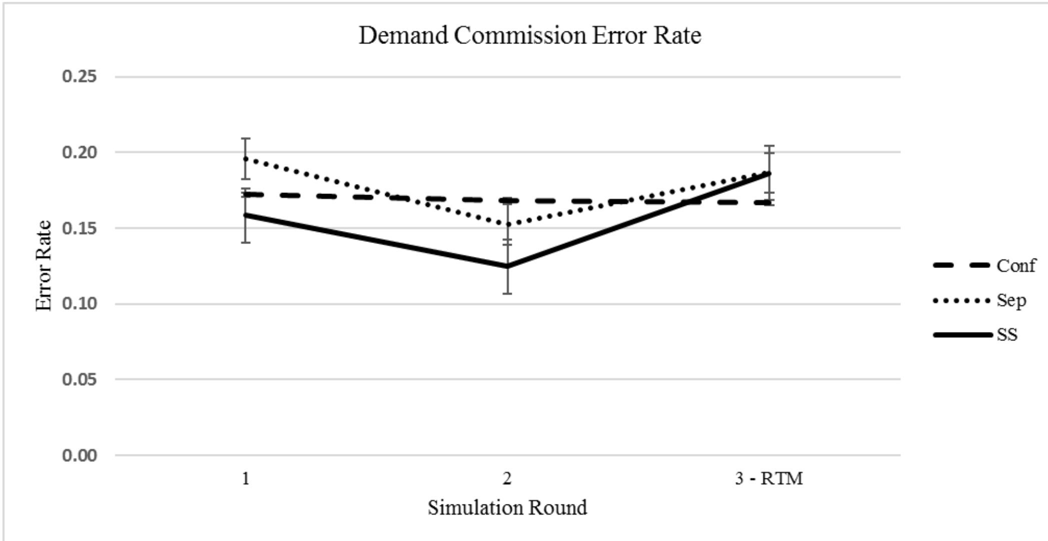


Figure 25.  Demand Commission Error Rate as a function of Display Type and Simulation Round

Results from the two-way mixed ANOVA found significant main effects for Condition $F(5,84) = 2.76$, $p = .024$, $\eta_p^2 = .141$, and Simulation Round, $F(1.75, 147.22) = 7.12$, $p = 0.02$, $\eta_p^2 = .078$, as well as a significant Condition x Simulation Round interaction $F(8.76, 147.22) = 5.04$, $p < .001$, $\eta_p^2 = .231$.  A second two-way mixed ANOVA featuring simulation rounds 1 & 2 also identified a significant main effect for conditions, $F(5,84) = 7.47$, $p < .001$, $\eta_p^2 = .308$.

Post-hoc contrasts investigating the significant main effect for Condition revealed no significant differences between Conditions (Figure 27).  Analysis of significant main effect for conditions in simulation rounds 1 and 2 revealed the Sep:No-DA and the Conf:No-DA had higher demand commission errors than each of the DA conditions (Table 6).  Further analysis found that with the exception of Sep:DA and SS:No-DA, all DA conditions were significantly different from all No-DA conditions in round 1 (Table 7).  Differences in demand commission error rates between conditions were no longer significant after round 1, indicating that the No-DA conditions improved relative to the DA conditions.

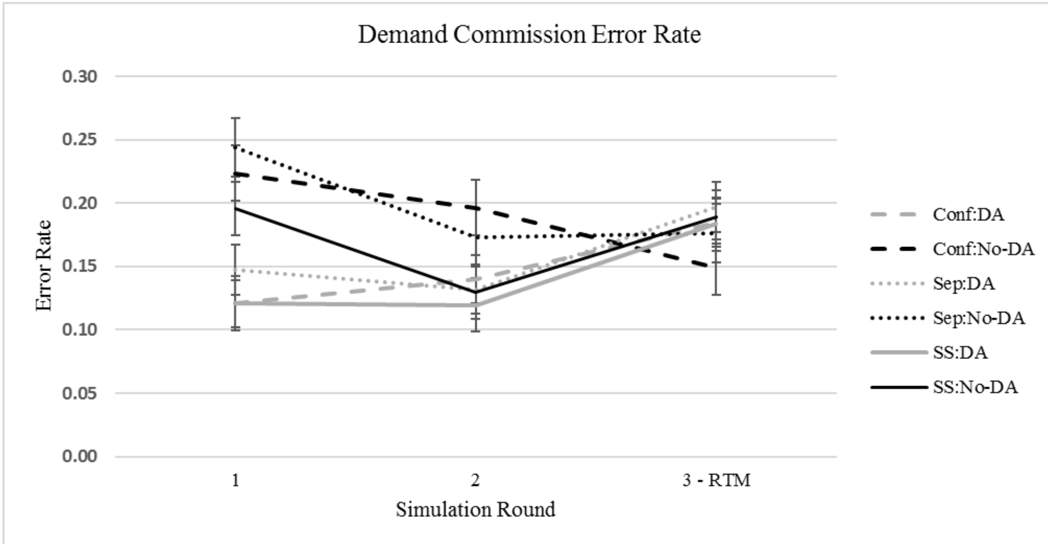


Figure 26. Demand Commission Error Rate as a function of Display Type:Decision Automation conditions and Simulation Round

| Condition (I) | Condition (J) | Mean Difference (I-J) | Std. Error | Sig. | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|
| Conf:No-DA | Conf:DA | .0797* | 0.02032 | 0.003 | 0.0183 | 0.1410 |
| | Sep:DA | .0702* | 0.02032 | 0.013 | 0.0088 | 0.1316 |
| | SS:DA | .0897* | 0.02032 | 0.000 | 0.0284 | 0.1511 |
| Sep:No-DA | Conf:DA | .0782* | 0.02032 | 0.003 | 0.0168 | 0.1396 |
| | Sep:DA | .0687* | 0.02032 | 0.016 | 0.0073 | 0.1301 |
| | SS:DA | .0883* | 0.02032 | 0.001 | 0.0269 | 0.1497 |

Table 6. Demand Commission Error Rate - Statistically significant pairwise comparisons of Display Type:Decision Automation conditions (Simulation Rounds 1 & 2)

| Simulation Round | Condition I | Condition J | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|---|
| 1 | Conf:DA | Conf:No-DA | -.103* | 0.023 | 0.000 | -0.173 | -0.033 |
| | | Sep:No-DA | -.124* | 0.023 | 0.000 | -0.194 | -0.053 |
| | | SS:No-DA | -.075* | 0.023 | 0.026 | -0.146 | -0.005 |
| | Sep:DA | Conf:No-DA | -.076* | 0.023 | 0.024 | -0.146 | -0.006 |
| | | Sep:No-DA | -.097* | 0.023 | 0.001 | -0.167 | -0.026 |
| | SS:DA | Conf:No-DA | -.103* | 0.023 | 0.000 | -0.173 | -0.032 |
| | | Sep:No-DA | -.123* | 0.023 | 0.000 | -0.194 | -0.053 |
| | | SS:No-DA | -.075* | 0.023 | 0.027 | -0.145 | -0.005 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Table 7. Demand Commission Error Rate Simulation Round - Statistically significant pairwise comparisons of Display Type:Decision Automation conditions in Simulation Round 1

Additional investigation identified differences in demand commission error rates between rounds. The No-DA conditions exhibited a general ability to improve, with the SS:No-DA , $t(84) = 3.46$, $p = .003$, and the Sep:No-DA, $t(84) = 3.72$, $p = .001$, improving from round 1 to round 2, and the Sep:No-DA, $t(84) = 2.62$, $p = .031$, and the Conf:No-DA, $t(84) = 2.87$, $p = .015$, improving from round 1 to round 3. The exception to this, being the significant increase in error rate for the SS:No-DA condition in the RTM round, $t(84) = -3.08$, $p = .017$. The SS:DA, $t(84) = -2.85$, $p = .008$, and the Sep:DA, $t(84) = -3.13$, $p = .007$, conditions also worsened in the RTM round, while the Conf:DA worsened from round 1 to round 3, $t(84) = -2.47$, $p = .047$. Generally, the No-DA conditions improved through practice while the DA conditions were more susceptible to the impacts of the RTM round.

### *Damage Omission Errors*

Analysis of damage omission errors revealed a statistically significant main effect for Simulation Round, $F(1.56,130.89) = 28.523$, $p = 0.001$, $\eta_p^2 = .253$, and a statistically significant interaction between Automation Type x Simulation Round, $F(1.56,130.89) = 7.46$, p = 0.002, $\eta_p^2 = .082$ (both reported with Greenhouse-Geisser correction). All other effects failed to reach statistical significance. A second three-way mixed ANOVA examining simulation rounds 1 & 2, identified significant a main effect for Automation Type, $F(1,84) = 5.07$, $p < .027$, $\eta_p^2 = .057$.

Investigation of the significant main effect for Simulation round revealed a significant increase in damage omission errors in the RTM round over the previous rounds. Post-hoc analyses indicated a significant difference between rounds 1 and 3, $t(84) = -6.00$, $p < .001$, and round 2 and 3, $t(84) = -5.69$, $p < .001$ (Figure 28).

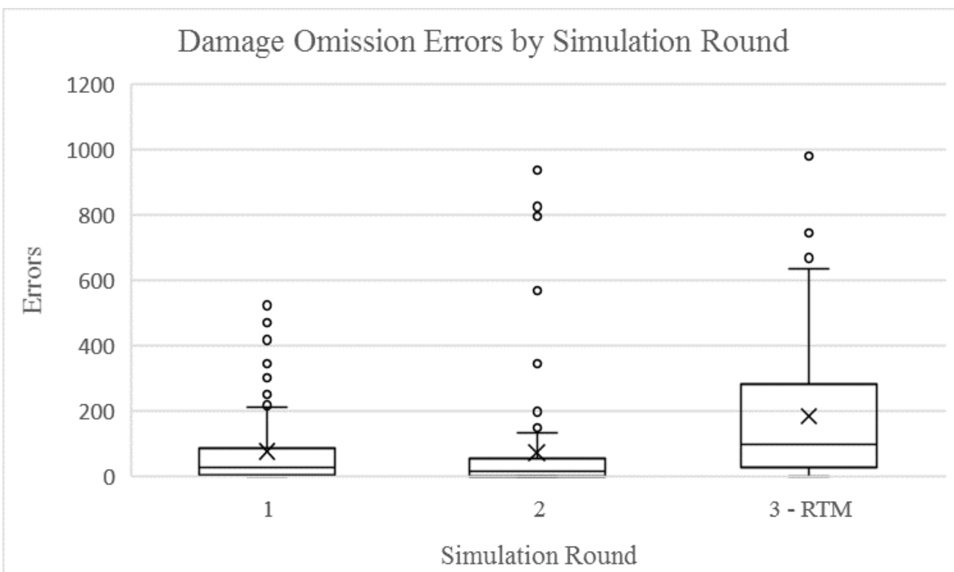


Figure 27. Demand Omission Errors as a function of Simulation Round

Post-hoc analyses were performed examining the results of the significant effect of the Automation Type x Simulation Round interaction (Figure 29). Pairwise comparisons found the DA group had lower demand omission errors in round 1, $t(84) = -2.94$, $p = .004$, but differences between AT levels did not reach statistical significance in round 2 or round 3. The DA group's damage omission errors increased significantly from round 2 to round 3, providing further evidence for the supporting effect of decision automation and the impact when assistance is reduced, $t(84) = -5.92$, $p < .001$.

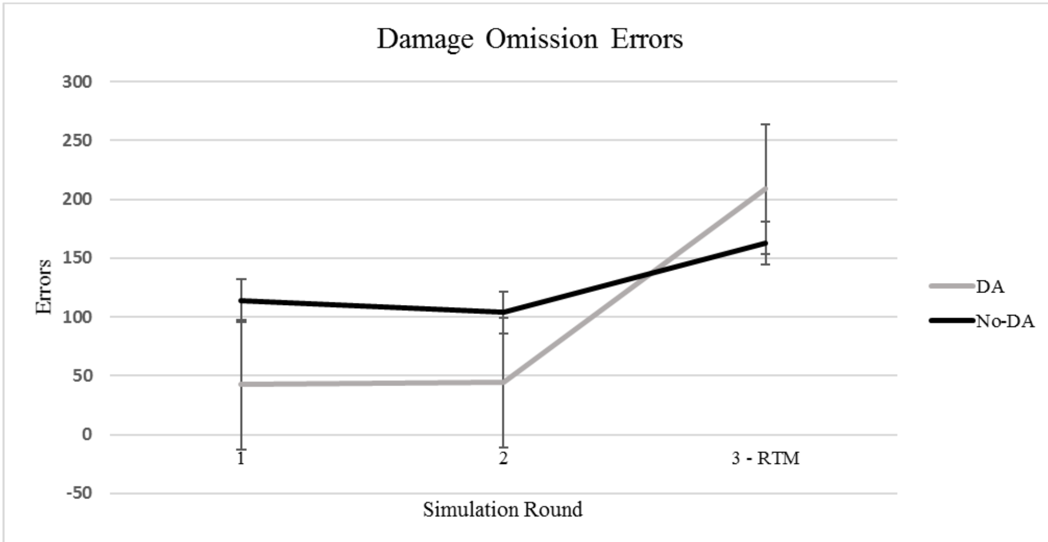


Figure 28. Damage Omission Errors as a function of Display Type and Simulation Round

The Condition x Simulation Round two-way mixed ANOVA found only a significant main effect was found for Simulation Round, $F(1.56, 130.87) = 28.52$, $p = .001$, $\eta_p^2 = .253$. The Condition x Simulation Round interaction effect nearly reached statistical significance, $F(7.79, 130.89) = 2.00$, $p = .053$, $\eta_p^2 = .106$ (Figure 30).

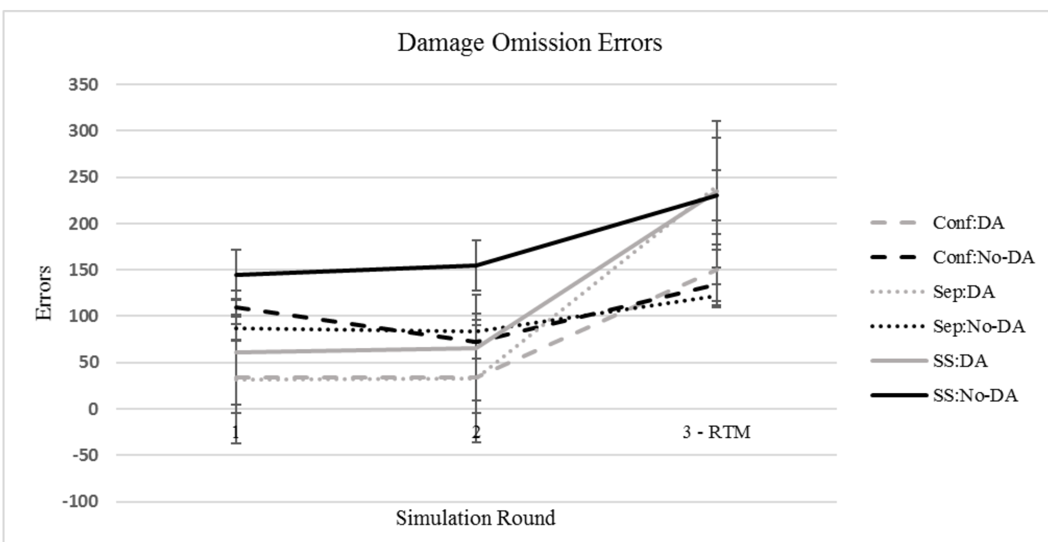


Figure 29. Damage Omission Errors as a function of Display Type:Decision Automation conditions and Simulation Round

***Damage Commission Error Rate***

Examination of the influence of the independent variables on participant damage commission error rates revealed a statistically significant main effect for Simulation Round, $F(2,168) = 7.44$, $p = .001$, $\eta_p^2 = .081$, and a statistically significant Automation Type x Simulation Round interaction, $F(2,168) = 10.48$, $p < .001$, $\eta_p^2 = .111$. A one-way ANOVA examining the difference between Automation Types and Display Types in the RTM round found a significant main effect for Automation Type, $F(1,84) = 18.25$, $p < .001$, $\eta_p^2 = .178$

A post-hoc analysis examining differences between simulation rounds found a significant improvement in damage commission error rates from simulation rounds 1 to round 2, $t(84) = 2.89$, $p = 0.005$. Analysis also found a significant increase in error rates from round 2 and 3, demonstrating the increased difficulty participant's experienced operating the simulation under reduced automation, $t(84) = -3.67$, $p = 0.004$. (Figure 31).

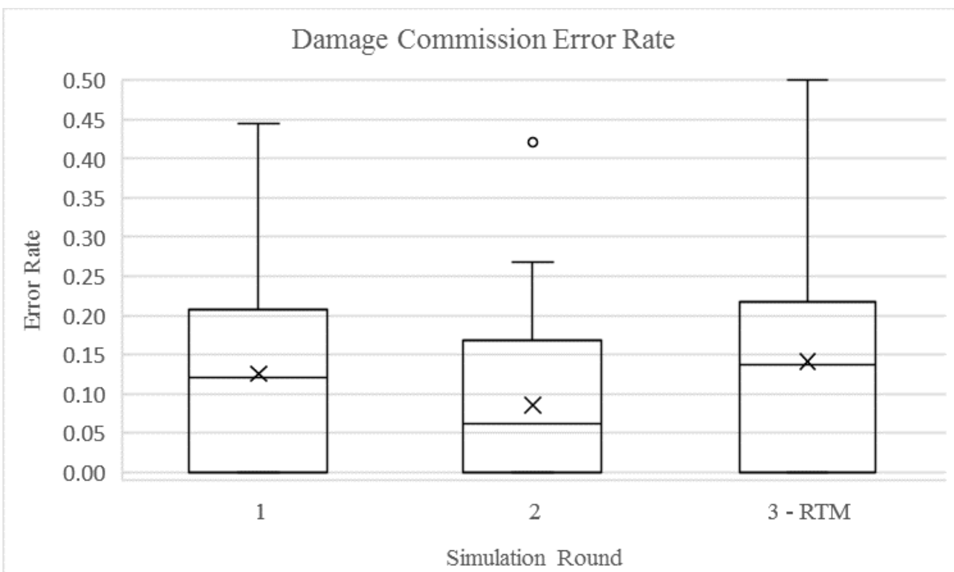


Figure 30. Damage Commission Error Rate as a function of Simulation Round

Post-hoc analysis of the AT x Simulation Round interaction revealed a significant reduction in damage commission error rate from round 1 to round 2 for the No-DA group, $t(84) = 2.89$, $p < .015$ (Figure 32). The DA group's error rates increased significantly in the RTM round, $t(84) = -4.80$, $p < .001$, and were significantly higher than the No-DA group's rates, $t(84) = 4.27$, *p* < .001. These findings indicate that prior system operation with the aid of decision automation negatively affected participants' ability to make the correct control changes necessary to remediate damage occurring within the system when automated assistance was reduced.

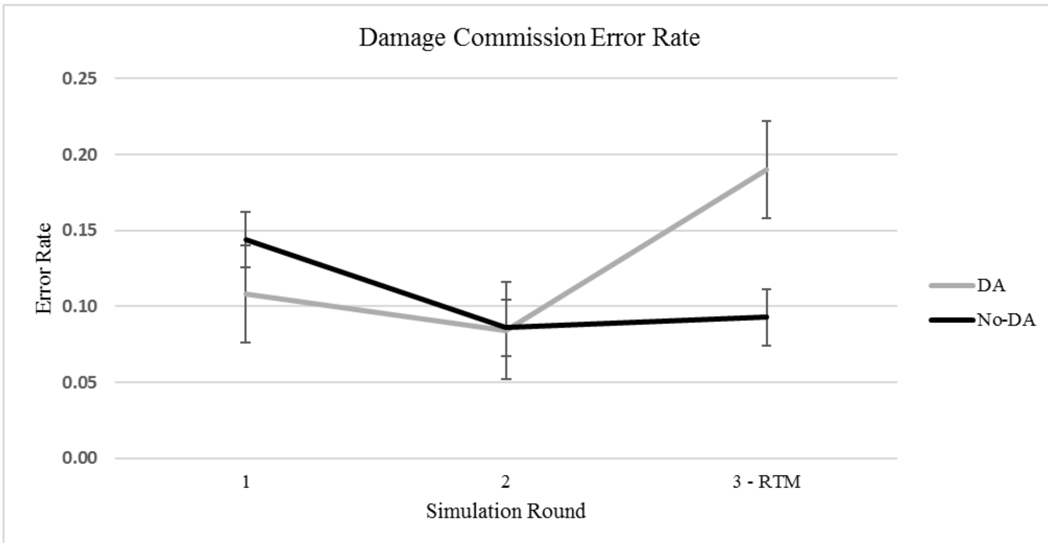


Figure 31. Damage Commission Error Rate as a function of Automation Type and Simulation Round

A two-way mixed ANOVA found a significant main effect for Simulation Round, $F(2,168) = 7.44$, $p = .001$, $\eta_p^2 = .081$, and a significant Condition x Simulation Round interaction $F(10, 168) = 2.37$, $p = 0.012$, $\eta_p^2 = .124$. Post-hoc analysis of the interaction revealed a significant decrease in damage commission error rate for the SS:No-DA condition from simulation round 1 to round 2, suggesting that the combination of explicit feedback and operating without decision support enabled participants' improvement, $t(84) = -2.63$, $p = 0.03$ (Figure 33). Error rates for the Conf:DA, $t(84) = -3.12$, $p = 0.008$, and the Sep:DA, $t(84) = -2.93$, $p = 0.013$, increased significantly in the RTM round, while the increase for the SS:DA condition nearly reached significance, $t(84) = -2.40$, $p = 0.055$. Significant differences between conditions occurred only in the RTM round, with the Sep:No-DA condition having lower error rates than the Sep:DA condition, $t(84) = 3.49$, $p = .011$, and the SS:DA condition, $t(84) = 3.03$, $p = .049$. These results provide insight into the significant difference between AT levels found in round 3.

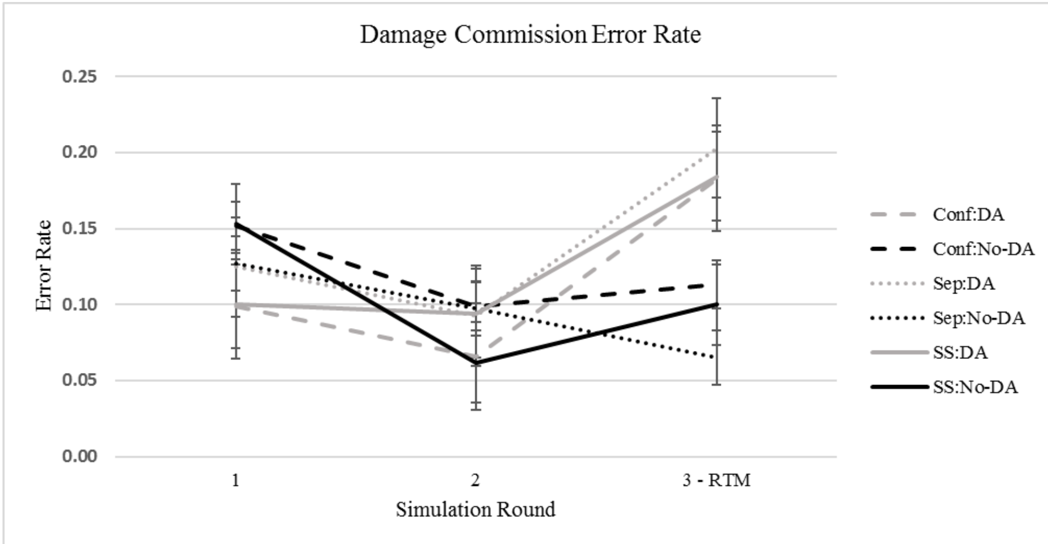


Figure 32. Damage Commission Error Rate as a function of Display Type:Decision Automation conditions and Simulation Round

*Assessment Score*

The results of a two-way ANOVA examining the influence of Automation Type, and Display Type on participant assessment scores found no statistically significant main effects or interactions for Automation Type, $F(1,84) = 1.56$, $p = .216$, $\eta_p^2 = .216$, Display Type, $F(2,84) = 1.93$, $p = .152$, $\eta_p^2 = .044$, or the AT x IT interaction, $F(2,84) = 2.23$, $p = .114$, $\eta_p^2 = .05$ (Figure 34). Additionally, a one-way ANOVA found no difference in assessment scores between individual conditions, $F(5,84) = 1.98$, $p = .091$, $\eta_p^2 = .105$.

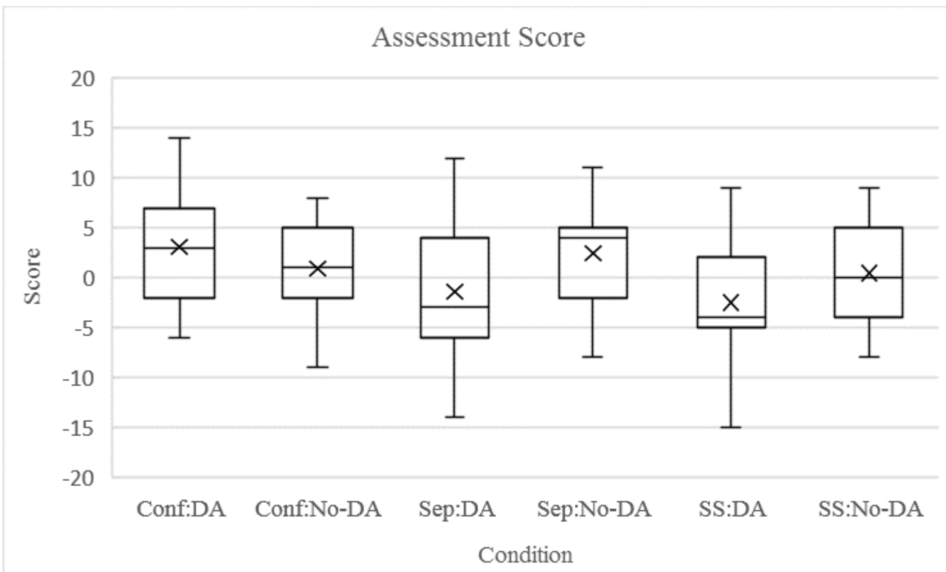


Figure 33. Assessment Score as a function of Display Type:Decision Automation conditions

## Workload Measurements

### *Reaction Time*

The results of a three-way mixed ANOVA examining the influence the independent variables on participant reaction time revealed statistically significant main effects for Automation Type, $F(1,84) = 6.56$, $p = .001$, $\eta_p^2 = .072$, and Simulation Round, $F(2,168) = 4.71$, $p = .010$, $\eta_p^2 = .053$. A one-way ANOVA examining the difference between Automation Types and Display Types in the RTM round found a significant main effect for Automation Type, $F(1,84) = 9.64$, $p = .003$, $\eta_p^2 = .103$. Further analysis did not find a significant Automation Type x Simulation Round interaction between rounds 2 and 3.

Analysis of the significant main effect for Simulation Round indicated that round 2 reaction times were lower than round 1, indicating that increased experience operating the system allowed participants to respond more quickly to the maintenance initiation prompt, $t(84) = 3.04$, $p = 0.009$ (Figure 35).

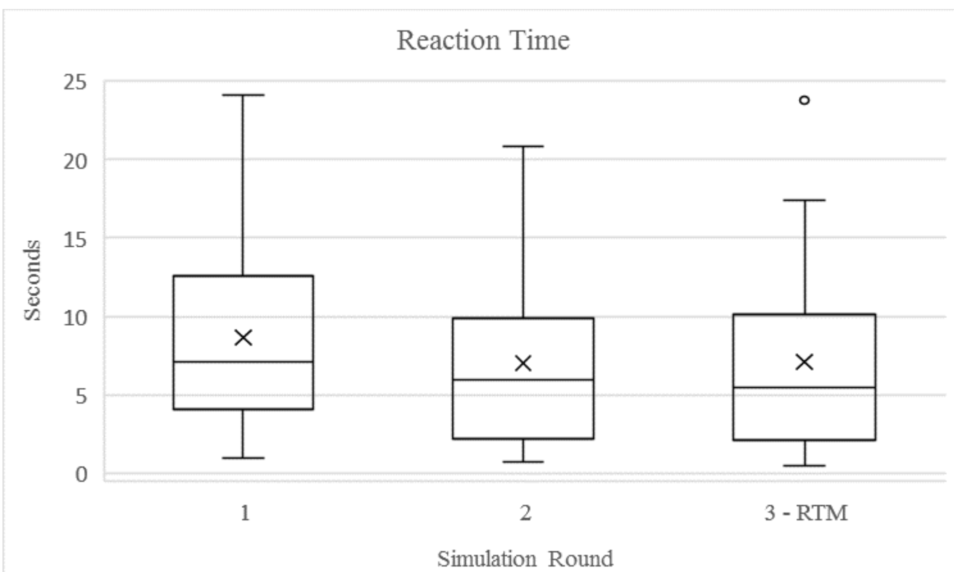


Figure 34. Reaction Time as a function of Simulation Round

Analysis of the significant main effect for Automation Type found the DA group had higher reaction time scores than the No-DA group, indicating that the presence of automated prompts that directed control changes slowed participant response to the appearance of the maintenance initiation prompt $t(84) = 2.56$, $p = 0.012$ (Figure 36). This finding was unexpected as the availability of decision automation was anticipated to reduce workload.

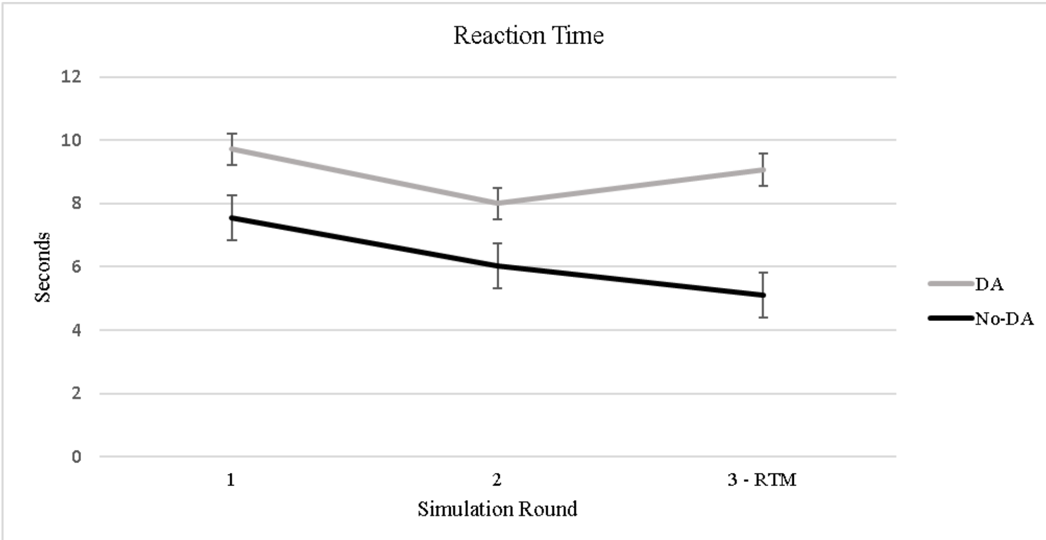


Figure 35. Reaction Time as a function of Automation Type and Simulation Round

A two-way mixed ANOVA featuring the Conditions and Simulation Rounds did not reveal any additional findings.

### ***Subjective Workload - NASA TLX***

*Mental Demand*

Analysis of participant mental demand revealed a statistically significant main effect for Simulation Round, $F(1.77, 148.77) = 9.41$, $p < .001$, $\eta_p^2 = .101$ (reported with Greenhouse-Geisser correction). Pairwise comparisons revealed a significant difference between round 1 and round 2, indicating participants experienced a reduction in mental demand with additional experience operating the simulation, $t(84) = 2.72$, $p = .024$ (Figure 37). Mental demand in the RTM round was also found to be higher than round 2, indicating that participants found operating the simulation with a reduction in automated assistance increased mental demand, $t(84) = -4.48$, $p < .001$.

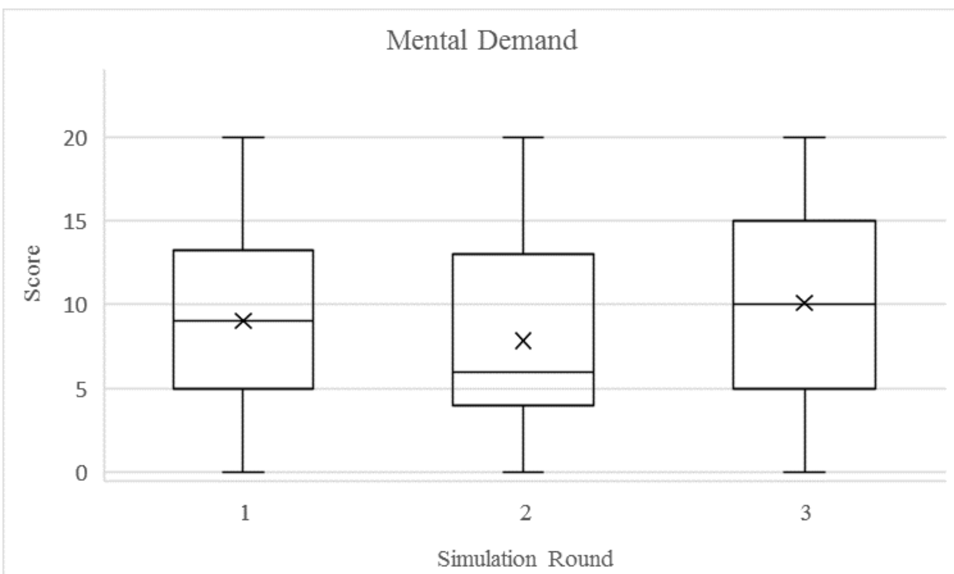


Figure 36. Mental Demand as a function of Simulation Round

*Physical Demand*

Analysis of physical demand revealed a significant main effect for Simulation Round, $F(1.63, 136.77) = 6.00$, $p = .006$, $\eta_p^2 = .067$ (reported with Greenhouse-Geisser correction). Post-hoc analysis found significant differences between round 1 and round 3, $t(84) = -2.64$, $p = .030$, and round 2 and round 3, $t(84) = -2.88$, $p = .005$ (Figure 38). These results indicate the additional practice afforded in round 2 did not serve to reduce physical demand, and the reduction of automated assistance experienced in the RTM round was more physically demanding than prior rounds with greater automated support.

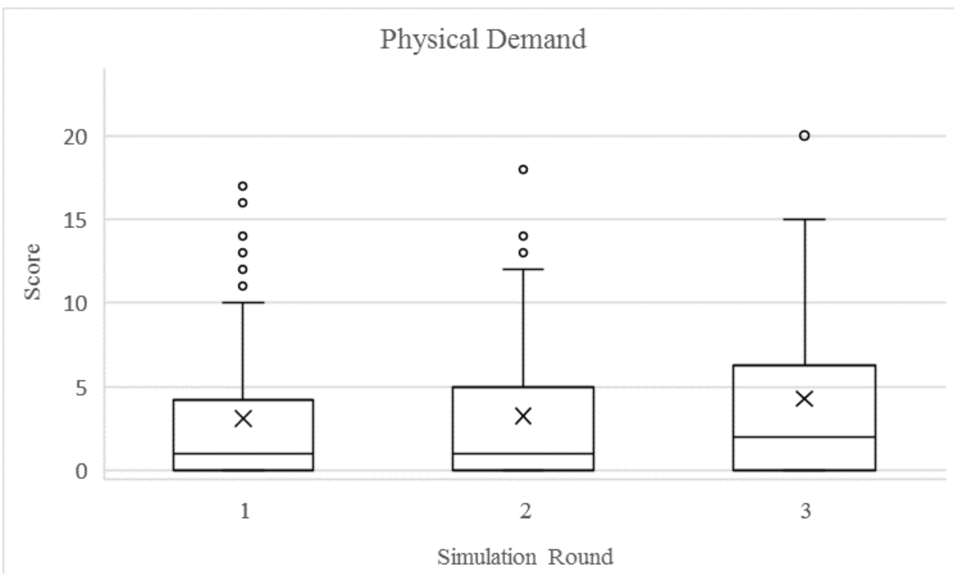


Figure 37. Physical Demand as a function of Simulation Round

*Temporal Demand*

The three-way mixed ANOVA examining temporal demand revealed a statistically significant main effect for Simulation Round, $F(1.18, 148.65) = 4.58$, $p = .015$, $\eta_p^2 = .052$ (reported with Greenhouse-Geisser correction). Subsequent pairwise analysis identified a significant difference between round 1 and round 2, indicating participants experienced a reduction in temporal demand with additional experience operating the simulation, $t(84) = 2.67$, $p = .027$ (Figure 39). Temporal demand in the RTM round was also found to be higher than round 2, indicating that participants found operating the simulation with reduced automated assistance increased temporal demand, $t(84) = -2.96$, $p < .012$.

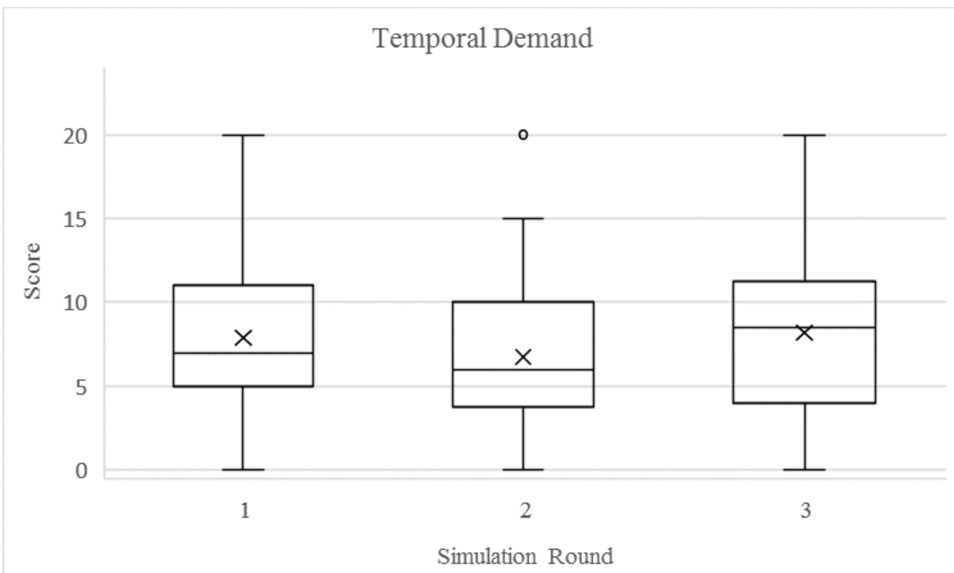


Figure 38. Temporal Demand as a function of Simulation Round

*Performance*

Analysis of participants' subjective performance revealed a statistically significant main effect for Simulation Round, $F(1.17, 145.03) = 5.70$, $p = .006$, $\eta_p^2 = .064$, and a significant effect for the Automation Type x Simulation Round interaction, $F(1.17, 145.03) = 6.68$, $p = .002$, $\eta_p^2 = .074$ (both results reported with Greenhouse-Geisser correction). A second three-way mixed ANOVA examining simulation rounds 1 & 2, identified significant a main effect for Automation Type, $F(1,84) = 4.94$, $p < .029$, $\eta_p^2 = .055$, and a significant AT x Simulation Round interaction, $F(1,84) = 8.09$, $p < .006$, $\eta_p^2 = .088$.

Post-hoc analysis the significant main effect for Simulation found that self-assessed performance suffered in the RTM round, as performance decreased between simulation rounds 2 and 3, $t(84) = -3.25$, $p = .005$ (Figure 40).

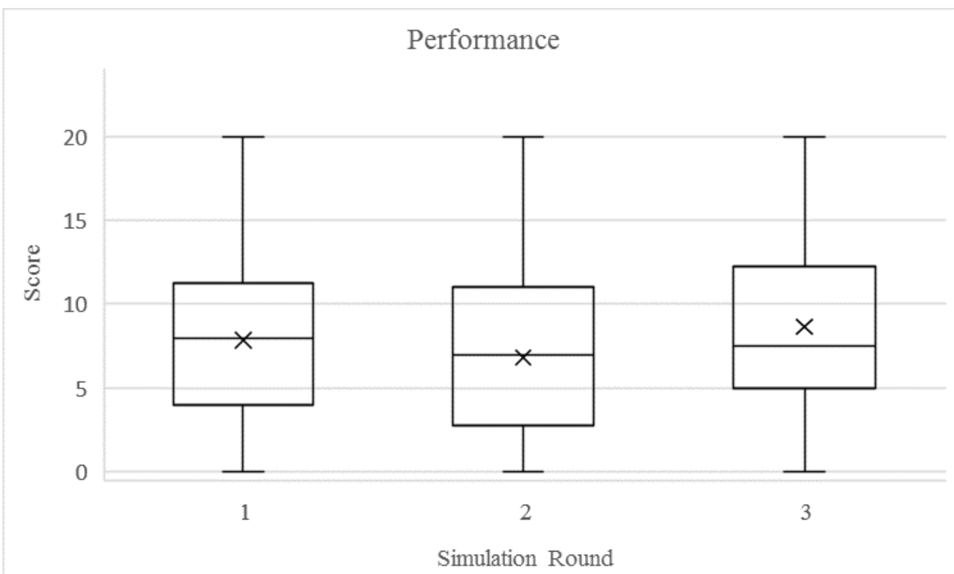


Figure 39. Performance as a function of Simulation Round

The basis for the significant for the AT x Simulation Round interaction and the main effect for simulation rounds 1 and 2 can be determined by examining Figure 41. The DA group had a lower (better) self-assessed performance score in round 1, $t(84) = -3.28$, $p = .002$, while the No-DA group decreased (improved) significantly from round 1 to round 2, $t(84) = 3.69$, $p = .001$, resulting in the difference performance scores between AT levels no longer being significant in round 2. These results indicate that participants using decision automation initially assessed their performance to be superior to those operating without, but the difference was eliminated with additional practice. Performance scores increased (worsened) in RTM round for the DA group, indicating the participants assessed their performance to be negatively impacted by the reduction of automated support, $t(84) = -3.23$, $p = .005$.

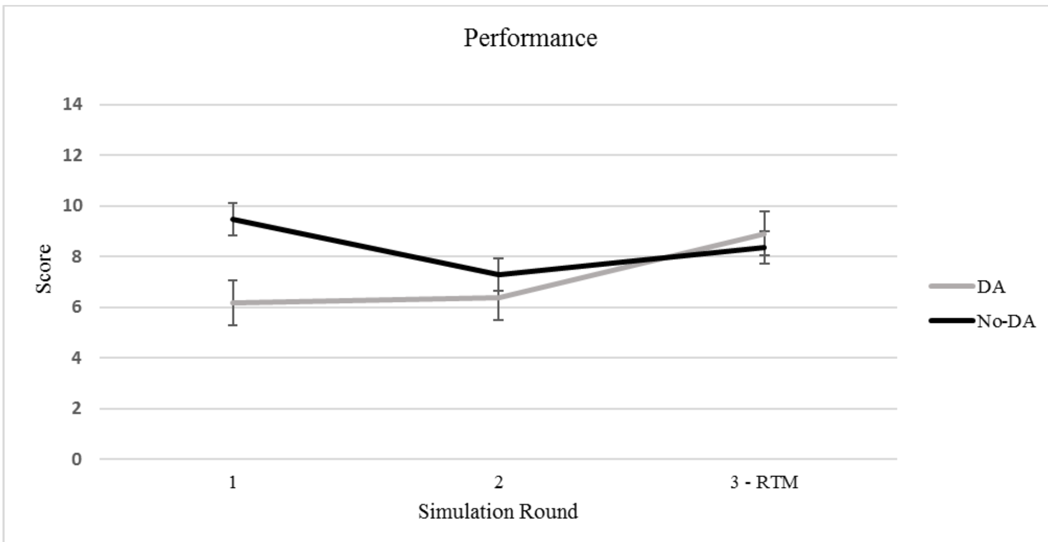


Figure 40. Performance as a function of Automation Type and Simulation Round

A two-way mixed ANOVA featuring Conditions and Simulations Rounds found significant main effect for Simulation Round, $F(1.73, 145.03) = 5.70$, $p = .006$, $\eta_p^2 = .064$, and a significant Condition x Simulation Round interaction $F(8.63, 145.03) = 2.62$, $p = .009$, $\eta_p^2 = .135$. The origins of the significant effects can be identified in Figure 42. The SS:DA group's round 1 performance is better than both the SS:No-DA group, $t(84) = 3.20$, $p = .033$, and the Sep:No-DA condition, $t(84) = 3.16$, $p = .029$. The SS:No-DA group's performance score improved in round 2, indicating the group's perception of improved performance, $t(84) = -3.42$, $p = .001$. Examination of the RTM round, revealed statistically significant differences in performance for the SS:DA condition from round 1 to round 3, $t(84) = -3.17$, $p = .006$, and from round 2 to round 3, $t(84) = -3.24$, $p = .005$.

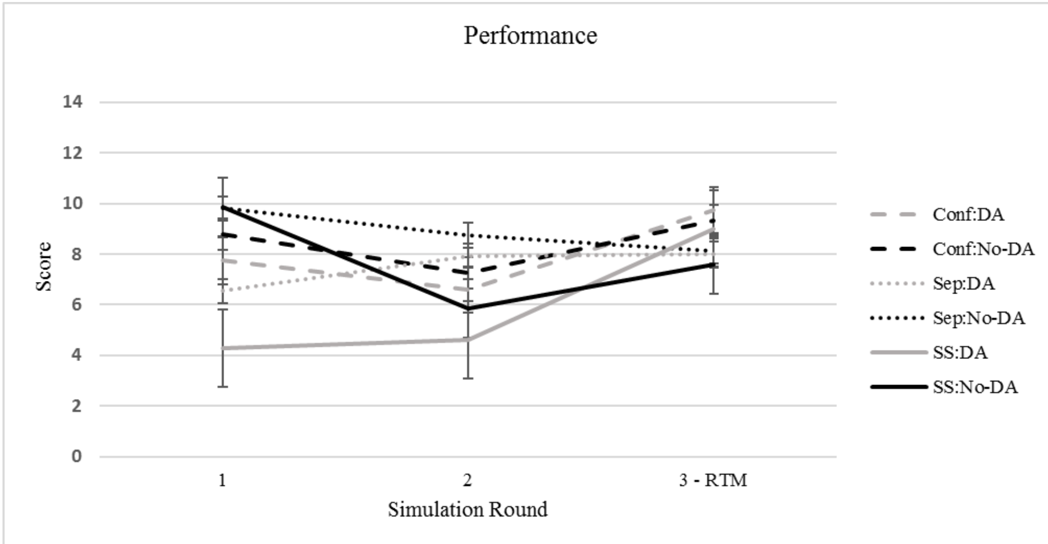


Figure 41. Performance as a function of Display Type:Decision Automation conditions and Simulation Round

*Effort*

Analysis of participants' self-assessed effort revealed statistically a significant main effects for Simulation Round, $F(1.84, 154.15) = 7.060$, $p = .002$, $\eta_p^2 = .078$ (reported with Greenhouse-Geisser correction). Post-hoc tests identified differences between simulation rounds 2 and 3, indicating that participants felt more effort was required during the RTM round, $t(84) = -3.62$, $p = .001$ (Figure 43).

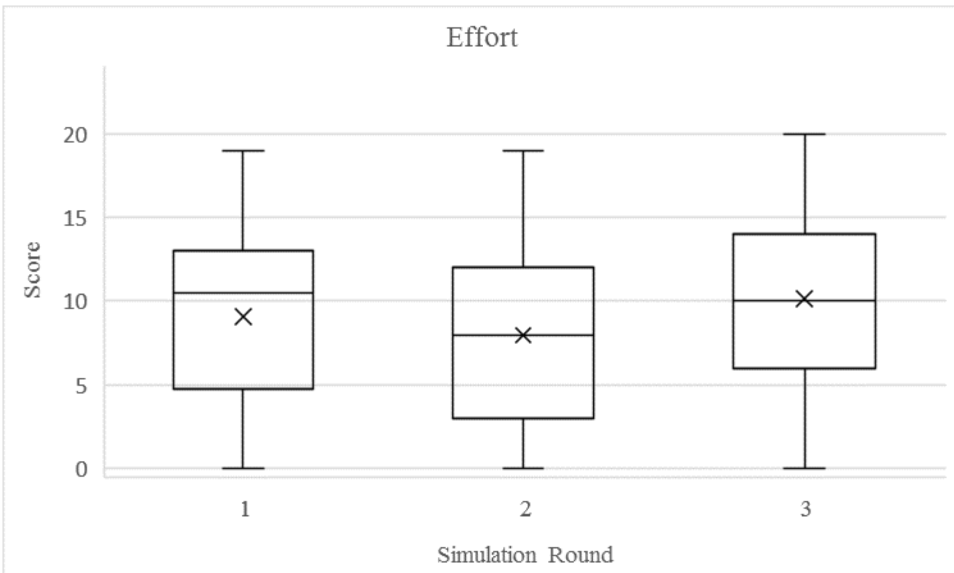


Figure 42. Effort as a function of Simulation Round

*Frustration*

The three-way mixed ANOVA examining participants' subjective performance revealed statistically significant main effects for Display Type, $F(2, 84) = 3.52$, $p = .034$, $\eta_p^2 = .077$, and Simulation Round, $F(1.63, 137.21) = 4.61$, $p = .017$, $\eta_p^2 = .052$ (reported with Greenhouse-Geisser correction). A significant effect was also identified for the Automation Type x Simulation Round interaction, $F(1.63, 137.21) = 4.60$, $p = .017$, $\eta_p^2 = .052$ (reported with Greenhouse-Geisser correction). A second three-way mixed ANOVA examining simulation rounds 1 & 2, identified significant a main effect for Display Type, $F(2,84) = 3.95$, $p = .023$, $\eta_p^2 = .086$

Investigation into the significant main effect for Simulation Round revealed an increase in frustration in the RTM round. Post-hoc tests identified differences in performance between simulation rounds 2 and 3, $t(84) = -3.44$, $p = .003$ (Figure 44).

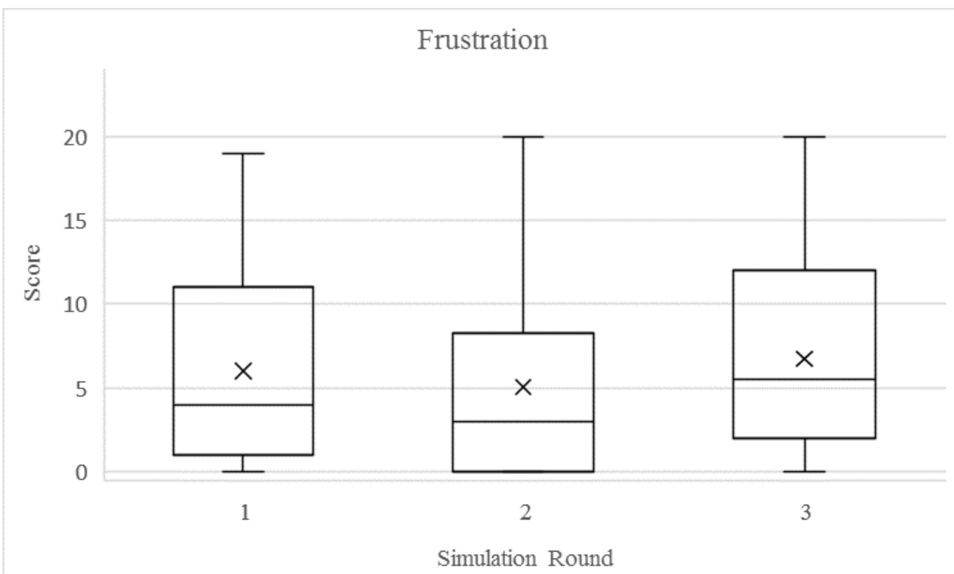


Figure 43. Frustration as a function of Simulation Round

Post-hoc analysis of the significant main effect for Display Type found that frustration was higher for the separable display than for the semantic-spatial, $t(84) = 2.65$, $p = .029$ (Figure 45). The availability of the real-time explanatory feedback provided in the semantic-spatial display reduced participant's frustration when compared to an otherwise identical display without this feedback.

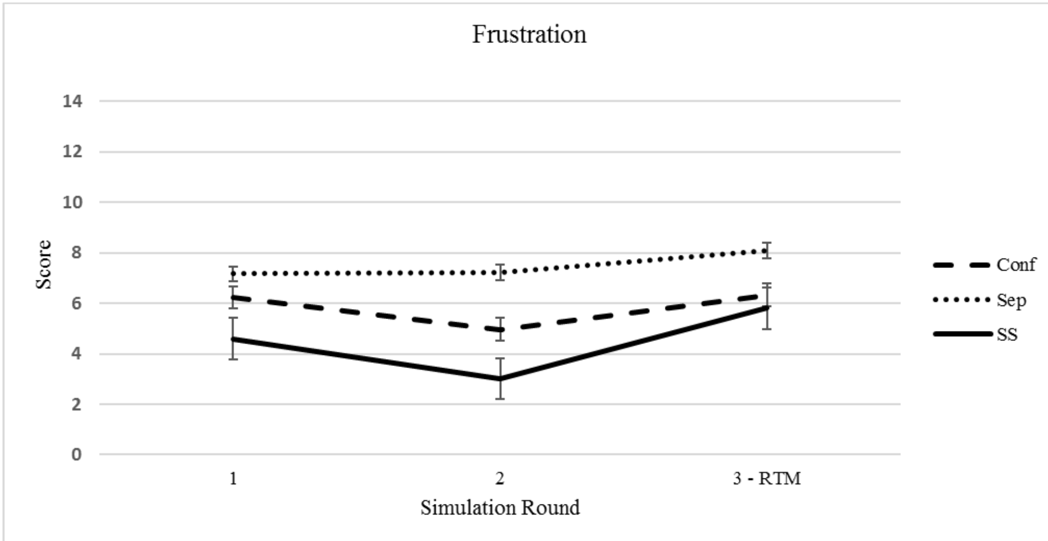


Figure 44. Frustration as a function of Display Type and Simulation Round

Post-hoc analysis of the Automation Type x Simulation Round interaction found the DA group's frustration score was lower than the No-DA group's in round 1, $t(84) = -2.04$, $p = .044$ (Figure 46). Frustration decreased for the No-DA group in round 2 as participants gained additional experience operating the simulation, $t(84) = 2.52$, $p = .041$. Higher levels of frustration were experienced by the DA group when operating under reduced automation in the RTM round when compare to round 1, $t(84) = -2.55$, $p = .038$, and round 2, $t(84) = -3.73$, $p = .001$.

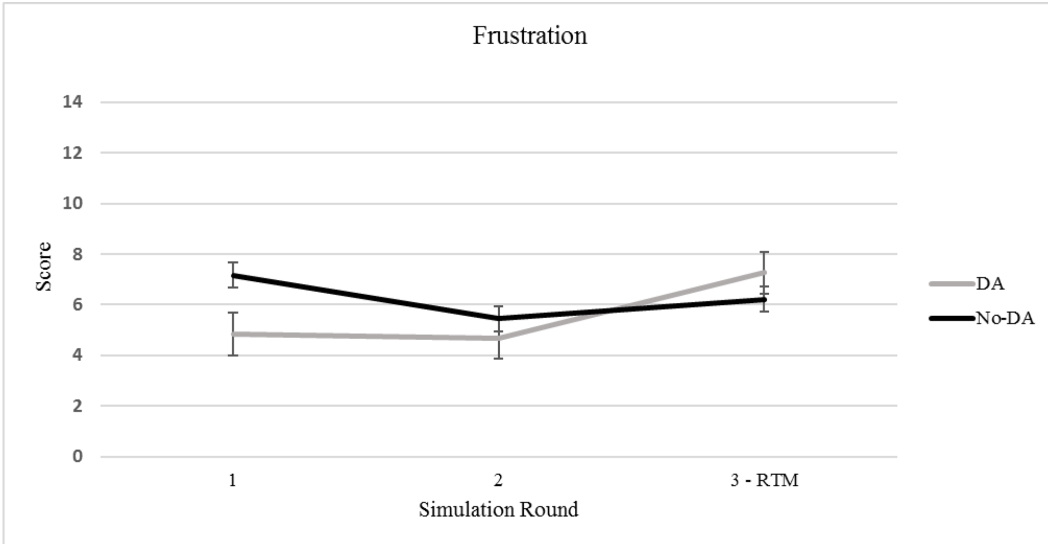


Figure 45. Frustration as a function of Automation Type and Simulation Round

A two-way mixed ANOVA featuring the Conditions and Simulation Rounds did not reveal any additional findings.

*Composite Score*

Analysis of the composite scores for the NASA TLX subjective workload measurements revealed a statistically significant main effect for Simulation Round, $F(1.64, 137.42) = 11.68$, $p < .001$, $\eta_p^2 = .122$ (reported with Greenhouse-Geisser correction). A significant effect was also identified for the Automation Type x Simulation Round interaction, $F(1.64, 137.42) = 3.74$, $p = .034$, $\eta_p^2 = .043$ (reported with Greenhouse-Geisser correction).

Investigation into the significant main effect for Simulation Round found in the three-way mixed ANOVA revealed that the subjective workload composite score decreased in round 2, then increased in the RTM round. Post-hoc tests identified differences in the composite score between Simulation Rounds 1 and 2, indicating that subjective workload decreased with additional practice operating the simulation, $t(84) = -3.31$, $p = .004$ (Figure 47). Similar to all of the other NASA TLX scores, the composite score increased as a result of the reduction in automated assistance in the RTM round, $t(84) = -4.59$, $p < .001$.

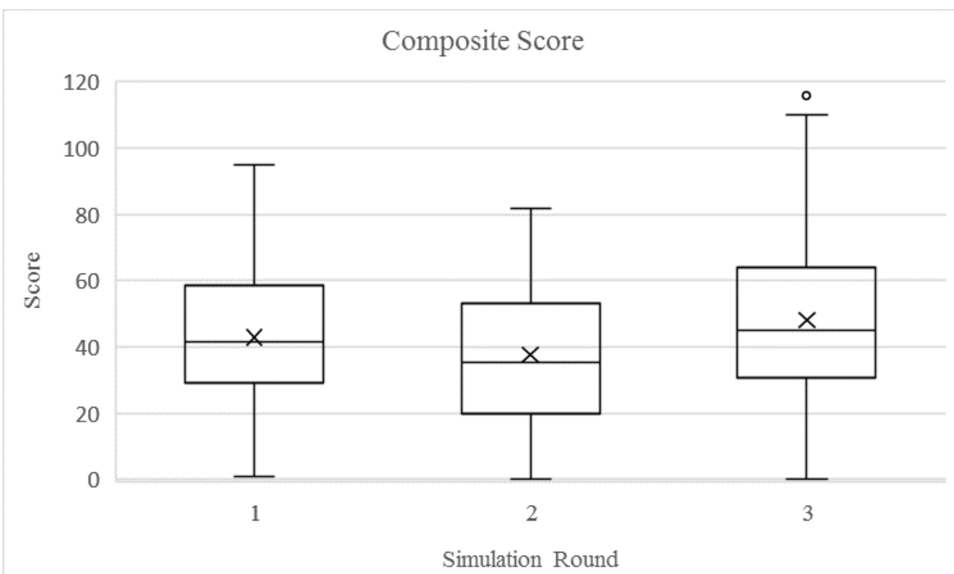


Figure 46. Composite Score as a function of Simulation Round.

Post-hoc analysis of the Automation Type x Simulation Round interaction found the DA group's composite score was lower than the No-DA group's in round 1, $t(84) = -2.2$, $p = .031$ (Figure 48). The composite score decreased for the No-DA group in round 2 as participants gained additional experience operating the simulation, $t(84) = 3.65$, $p = .001$. The DA group's composite score was higher in the RTM round than both round 1, $t(84) = -3.12$, $p = .007$, and round 2, $t(84) = -4.17$, $p < .001$.

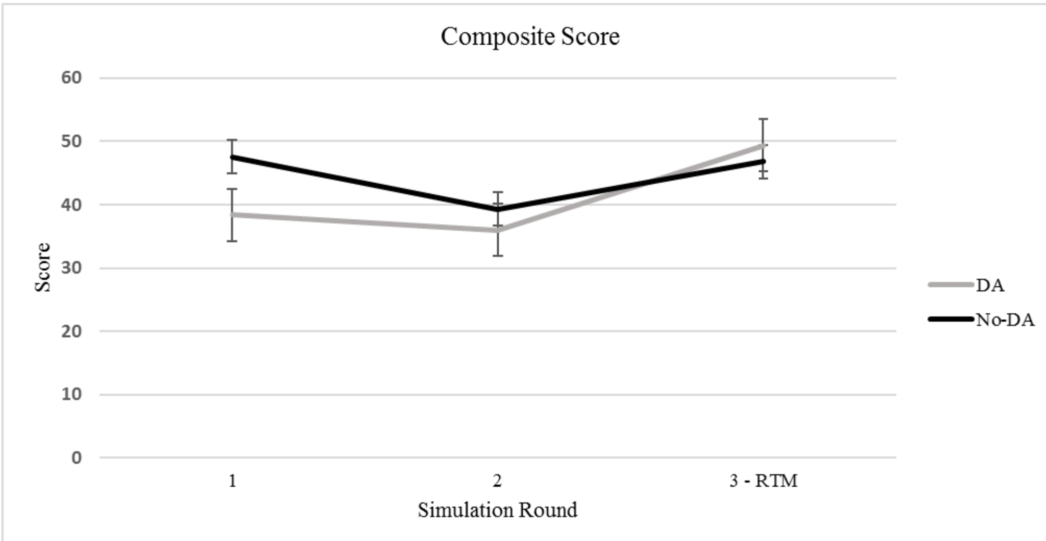


Figure 47. Composite Score as a function of Automation Type and Simulation Round

**Measuring the relationship between workload, understanding, and return-to-manual performance**

***Net Income***

*Total Population*

A significant regression equation was found $F(2,87) = 24.16$, $p < .001$, with an adjusted $R^2 = .342$, when analyzing the full participant population (N = 90). Participants' predicted RTM delta for net income is equal to -1649145.048 + 5654.326 (Demand Omission Errors – Round 1) + 86754.521 (Assessment Score). The predicted RTM Delta for net income increased by $5,654.33 for each additional round 1 demand omission error ($\beta = .572$, $p < .001$, CI [3941.3, 7367.4]), and $87,754.52 for each correct answer on the assessment ($\beta = .291$, $p = .001$, CI [35087.9, 138421.2]).

*Automation Type – Decision Automation*

A significant regression equation was found $F(4,40) = 9.23$, $p < .001$, with an adjusted $R^2 = .428$, when analyzing the participants (N = 45) who operated the simulation with the aid of decision automation. Participant's predicted RTM Delta for net income is equal to -1824110.252 + 4000.105 (Demand Omission Errors – Round 1) + 92194.487 (Assessment Score) + 10636846.94 (Demand Commission Error Rate – Round 2) – 34434.918 (Composite Score – Round 2). The predicted RTM Delta for net income increased by $4,000.11 for each additional demand omission error in round 1 ($\beta = .346$, $p = .024$, CI [550.84, 7449.37]), $92,194.49 for each correct answer on the assessment ($\beta = .395$, $p = .002$, CI [36862.98, 147526]), $106,368.47 for each demand commission error rate percentage point increase in round 2 ($\beta = .448$, $p = .006$, CI [3239703.88, 18033990]), and decreased $34,434.92 for each point increase in the NASA TLX composite score in round 2 ($\beta = -.472$, $p = .001$, CI [-53523.82, -15346.02]).

*Automation Type – No Decision Automation*

A significant regression equation was found $F(1,43) = 9.81$, $p = .003$, with an adjusted $R^2 = .167$, when analyzing the participants (N = 45) who operated the simulation without the aid of decision automation. Participants' predicted RTM Delta for net income is equal to -769333.311 + 3892.16 (Demand Omission Errors – Round 1). The predicted RTM delta for net income increased by $3,892.16 for each additional demand omission error in round 1 ($\beta$ = .431, $p$ = .003, CI [1385.91, 6398.41]).

*Display Type – Configural*

A significant regression equation was found $F(3,25) = 23.54$, $p < .001$, with an adjusted $R^2 = .700$, when analyzing the participants (N = 30) who operated the simulation with the configural display type. Participants' predicted RTM Delta for net income is equal to -1276399.690 + 13414.271 (Demand Omission Errors – Round 1) – 209337.034 (Physical Demand – Round 2) – 194152.871 (Frustration – Round 2). The predicted RTM Delta for net income increased by $13,414 for each additional demand omission error in round 1 ($\beta$ = 1.159, $p < .001$, CI [9878.922, 16949.62]), and decreased $209,337.04 for each addition point on the NASA TLX physical demand score in round 2, ($\beta$ = -.399, $p$ = .019, CI [-323082.994, -95591.074]), and decreased $194,152.87 for each additional point on the NASA TLX frustration score in round 1($\beta$ = -.535, $p$ = .001, CI [-302399.011, -85906.731]) .

*Display Type – Separable*

A significant regression equation was found $F(1,28) = 6.42$, $p = .017$, with an adjusted $R^2 = .158$, when analyzing the participants (N = 30) who operated the simulation with the separable display type. Participants' predicted RTM Delta for net income is equal to -2077103.54 + 9588719.55 (Demand Commission Error Rate – Round 1). The RTM Delta for net income increased by $95,887.19 for each percentage point increase in demand commission error rate in round 1 ($\beta$ = .432, $p$ = .017, CI [1839387, 17338052.10]).

*Display Type – Semantic-Spatial*

A significant regression equation was found $F(5,24) = 10.49$, $p < .001$, with an adjusted $R^2 = .620$, when analyzing the participants (N = 30) who operated the simulation with the semantic-spatial display type. Participants' predicted RTM Delta for net income is equal to -1248545.13 + 10911947.16 (Demand Commission Error Rate – Round 1) + 7512.557 (Demand Omission Errors – Round 2) – 68576.33 (Reaction Time – Round 1) – 114025.16 (Effort – Round 2) – 93460.71 (Performance – Round 1). The predicted RTM Delta for net income increased by

\$109,119.48 for each percentage point increase in demand commission error rate in round 1 ($\beta$ = .561, $p$ = .001, CI [4699628.88, 17124265.43]), \$7,512.56 for each additional demand omission error in round 2 ($\beta$ = .583, $p$ = .004, CI [2590.33, 12434.78]), and decreased \$68,576.33 for each additional second of reaction time in round 1 ($\beta$ = -.349, $p$ = .008, CI [-117217.304, -19935.35]), \$114,025 for each additional point for the NASA TLX effort score in round 2 ($\beta$ = -.484, $p$ = .001, CI [-176321.17, -51729.12]), and \$93,460.71 for each additional point in the NASA TLX performance score in round 1 ($\beta$ = -.392, $p$ = .036, CI [-180166.41, -6755]).

### ***Production Delta***

#### *Total Population*

A significant regression equation was found $F(2,87) = 15.35$, $p < .001$, with an adjusted $R^2 = .244$, when analyzing the full participant population (N = 90). Participants' predicted RTM Delta for production delta is equal to 6.158 - .041 (Demand Omission Errors – Round 1) + 1.134 (Physical Demand – Round 2). The RTM Delta for production delta decreased by .041 for each additional round 1demand omission error ($\beta$ = -.443, $p$ < .001, CI [-.058, -.024]), and increased 1.134 for each additional point in the NASA TLX physical demand score in round 2 ($\beta$ = .278, $p$ = .003, CI [.386, 1.883]).

#### *Automation Type – Decision Automation*

A significant regression equation was found $F(2,42) = 27.31$, $p < .001$, with an adjusted $R^2 = .545$, when analyzing the participants (N = 45) who operated the simulation with the aid of decision automation. Participants' predicted RTM Delta for production delta is equal to 4.534 - 4.695 (Physical Demand – Round 1) + 5.005 (Physical Demand – Round 2). The predicted RTM Delta for production delta increased by 5.01 for each additional point in the NASA TLX physical demand score in round 2 ($\beta$ = 1.591, $p$ < .001, CI [3.635, 6.376]), and decreased 4.70 for each additional point in the NASA TLX physical demand score in round 1 ($\beta$ = -1.461, $p$ < .001, CI [-6.095, -3.294]).

*Automation Type – No Decision Automation*

A significant regression equation was found $F(1,43) = 4.78$, $p = .034$, with an adjusted $R^2 = .079$, when analyzing the participants (N = 45) who operated the simulation without the aid of decision automation. Participants' predicted RTM Delta for production delta is equal to 3.429 - .030 (Demand Omission Errors – Round 1). The RTM Delta for production delta decreased by .030 for each additional demand omission error in round 1 ($\beta = -.316$, $p = .034$, CI [-.057, -.002]).

*Display Type – Configural*

A significant regression equation was found $F(3,26) = 22.74$, $p < .001$, with an adjusted $R^2 = .692$, when analyzing the participants (N = 30) who operated the simulation with the configural display type. Participants' predicted RTM Delta for production delta is equal to 9.715 - .129 (Demand Omission Errors – Round 1) + 2.143 (Physical Demand – Round 2) + 1.926 (Frustration – Round 1). The RTM Delta for production delta decreased by .129 for each additional demand omission error in round 1 ($\beta = -1.152$, $p < .001$, CI [-.163, -.094]), and increased 2.143 for each additional point in the NASA TLX performance score in round 2 ($\beta = .422$, $p = .001$, CI [1.030, 3.255]), and 1.926 for each additional point in the NASA TLX frustration score in round 1 ($\beta = .550$, $p = .001$, CI [.867, 2.985]).

*Display Type – Separable*

A significant regression equation was found $F(2,27) = 7.78$, $p = .002$, with an adjusted $R^2 = .319$, when analyzing the participants (N = 30) who operated the simulation with the separable display type. Participants' predicted RTM Delta for production delta is equal to 2.892 - .201 (Damage Omission Errors – Round 1) + .134 (Damage Omission Errors – Round 2). The predicted RTM Delta for production delta decreased by .201 for each additional damage omission error in round 1 ($\beta = -1.010$, $p = .001$, CI [-.307, -.096]), and increased .134 for each additional damage omission error in round 2 ($\beta = .753$, $p = .007$, CI [.040, .227]).

*Display Type – Semantic-Spatial*

A significant regression equation was found $F(3,26) = 22.77$, $p < .001$, with an adjusted $R^2 = .692$, when analyzing the participants (N = 30) who operated the simulation with the semantic-spatial display type. Participants' predicted RTM Delta for production delta is equal to 9.923 -117.984 (Demand Commission Error Rate – Round 1) + 1.227 (Mental Demand – Round 1) + .511(Reaction Time – Round 2). The RTM Delta for production delta decreased by 1.18 for each percentage point increase in the demand commission error rate in round 1 ($\beta = -.852$, $p < .001$, CI [-151.193, -84.776]), and increased 1.227 for each additional point for the NASA TLX mental demand score in round 1($\beta = .674$, $p < .001$, CI [.792, 1.662]), and increased .511 for each additional second in round 2 reaction time ($\beta = .350$, $p = .002$, CI [.200, .821]).

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***Repair Costs***

*Total Population*

A significant regression equation was found $F(4,85) = 10.33$, $p < .001$, with an adjusted $R^2 = .296$, when analyzing the participant population (N = 90). Participants' predicted RTM Delta for repair costs is equal to 600765.959 – 1342.908 (Demand Omission Errors – Round 1) – 2428.502 (Damage Omission Errors – Round 2) – 30145.508 (Assessment Score) + 2173.656 (Damage Omission Errors – Round 1). The RTM Delta for repair costs increased by $2,173.66 for each additional damage omission error in round 1 ($\beta = .397$, $p = .010$, CI [539.995, 3807.318]), and decreased $1342.91 for each additional demand omission error in round 1 ($\beta = -.376$, $p < .001$, CI [-2004.100, -681.716]), $2428.50 for each additional damage omission error in round 2 ($\beta = -.651$, $p < .001$, CI [-3529.419, -1327.586]), and $30,145.51 for each correct answer on the assessment ($\beta = -.280$, $p = .003$, CI [-49731.519, -10559.496]).

*Automation Type – Decision Automation*

A significant regression equation was found $F(2,42) = 8.76$, $p = .001$, with an adjusted $R^2 = .261$, when analyzing the participants (N = 45) who operated the simulation with the aid of decision automation. Participants' predicted RTM Delta for repair costs is equal to 544606.411 – 2651.54 (Damage Omission Errors – Round 2) - 30760.357 (Assessment Score). The predicted RTM Delta for repair costs decreased by $2,651.54 for each additional round 2 demand omission error ($\beta$ = .493, $p$ < .001, CI [-4071.591, -1231.482]), and $30,760.36 for each additional point on the assessment ($\beta$ = -.302, $p$ = .026, CI [-57676.995, -3843.718]).

*Automation Type – No Decision Automation*

A significant regression equation was found $F(1,43) = 9.28$, $p = .004$, with an adjusted $R^2$ = .158, when analyzing the participants (N = 45) who operated the simulation without the aid of decision automation. Participants' predicted RTM delta for repair costs is equal to 621525.048 – 47288.656 (Mental Demand – Round 1). The RTM delta for repair costs decreased by $47,288.66 for each additional point for the NASA TLX mental demand score in round 1($\beta$ = -.421, $p$ = .004, CI [-78591.127, -15986.185]).

*Display Type – Configural*

A significant regression equation was found $F(1,28) = 5.48$, $p = .027$, with an adjusted $R^2$ = .134, when analyzing the participants (N = 30) who operated the simulation with the configural display type. Participants' predicted RTM Delta for repair costs is equal to 509626.888 – 34041.282 (Effort – Round 1). The RTM Delta for repair costs decreased by $34,041.28 for each additional point for the NASA TLX effort score in round 1 ($\beta$ = -.405, $p$ = .027, CI [-63818.891, -4263.673]).

*Display Type – Separable*

A significant regression equation was found $F(1,28) = 7.04$, $p = 0.13$, with an adjusted $R^2$ = .172, when analyzing the participants (N = 30) who operated the simulation with the separable display type. Participants' predicted RTM Delta for repair costs is equal to 79793.485 – 3110402.771(Demand Commission Error Rate – Round 2). The RTM Delta decreased by $31,104.02 for each percentage point increase in the demand commission error rate in round 2 ($\beta$ = -.448, $p$ = .013, CI [-5512388.189, -708417.352]).

*Display Type – Semantic-Spatial*

A significant regression equation was found $F(1,28) = 10.30$, $p = .003$, with an adjusted $R^2 = .243$, when analyzing the participants (N = 30) who operated the simulation with the semantic-spatial display type. Participants' predicted RTM Delta for repair costs is equal to 746015.052 - .4540.203 (Demand Omission Errors – Round 2). The RTM Delta for repair costs decreased by $4,540.20 for each additional demand omission error in round 2 ($\beta = -.518$, $p = .003$, CI [-7438.729, -1641.678]).

The results of the multiple regression models were summarized (Table 8) for simplification, with the standardized beta coefficients, adjusted $R^2$, $F$, and $N$, provided for each.

Table 8. Summary of Stepwise Multiple Regression Analysis for Variables Predicting Performance RTM Delta's

| | Repair Costs | | | | | | Production Delta | | | | | | Net Income | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | All | DA | No-DA | Conf | Sep | SS | All | DA | No-DA | Conf | Sep | SS | All | DA | No-DA | Conf | Sep | SS |
| Assessment Score | -.280* | -.302 | | | | | | | | | | | 0.291* | .395* | | | | |
| Simulation Round 1 | | | | | | | | | | | | | | | | | | |
| Demand Omission Errors | -.376* | | | | | | -.443* | | -.316 | -1.152* | | | 0.572* | .345 | .431* | 1.159* | | |
| Damage Omission Errors | .397 | | | | | | | | | | -1.010* | | | | | | | |
| Demand Commission Error Rate | | | | | | | | | | | | -.852* | | | | | .432 | .561* |
| Reaction Time | | | | | | | | | | | | | | | | | | -.349* |
| Effort | | | | -.405 | | | | | | | | | | | | | | |
| Physical | | | | | | | | -1.461* | | | | | | | | | | |
| Mental Demand | | | -.421* | | | | | | | | | .647* | | | | | | |
| Performance | | | | | | | | | | | | | | | | | | -.392 |
| Simulation Round 2 | | | | | | | | | | | | | | | | | | |
| Demand Omission Errors | | | | | | -.518* | | | | | | | | | | | | .583* |
| Damage Omission Errors | -.651* | -.493* | | | | | | | | | .753* | | | | | | | |
| Demand Commission Error Rate | | | | | -.448 | | | | | | | | | .448* | | | | |
| Reaction Time | | | | | | | | | | | | .350* | | | | | | |
| Effort | | | | | | | | | | | | | | | | | | -.484* |
| Physical | | | | | | | .278* | 1.591* | | .422* | | | | | | -.399* | | |
| Frustration | | | | | | | | | | .550* | | | | | | -.535* | | |
| Composite Score | | | | | | | | | | | | | | -.472* | | | | |
| Adjusted $R^2$ | .296 | .261 | .158 | .134 | .172 | .243 | .244 | .545 | .079 | .692 | .319 | .692 | .342 | .428 | .167 | .700 | .158 | .620 |
| $F$ | 10.33* | 8.76* | 9.28* | 5.48 | 7.04 | 10.30* | 15.35* | 27.31* | 4.78 | 22.74* | 7.78* | 22.77* | 24.16* | 9.23* | 9.81* | 23.54* | 6.42 | 10.49* |
| N | 90 | 45 | 45 | 30 | 30 | 30 | 90 | 45 | 45 | 30 | 30 | 30 | 90 | 45 | 45 | 30 | 30 | 30 |

$\beta$ Increase in dependent variable predicts improved RTM Delta performance
$\beta$ Decrease in dependent variable predicts improved RTM Delta performance
All values are significant < .05, * indicates $p$ < .01

# Discussion

## Automation Types

Several significant findings were identified throughout the course of this experiment, confirming and extending our understanding of how Automation and Display Types influence novice-level participants' ability to manage dynamic systems under normal and return-to-manual scenarios. To begin, a general alignment with prior automation research was found, identifying that higher levels of automation improved performance and reduced workload, and that negative consequences of automation were more likely to occur when the degree of automation provided crosses the critical boundary between information analysis and decision selection (Onnasch et al., 2014; Wickens et al., 2010). The results also begin to answer the first research question, finding that variations in Automation Types influenced participant's implicit understanding of the system. In addition, the results provide new insight into how the availability of decision automation may limit experience when the system is in certain states, and how this may contribute to a diminished ability to make the corrections necessary in a return-to-manual scenario.

When operating with the aid of automation (Simulation Rounds 1 & 2), DA level participants demonstrated higher performance (net income, production delta), lower subjective workload (performance), and exhibited a better implicit understanding of the system (demand omission errors, demand commission error rate, damage omission errors) than their No-DA counterparts. Examination of individual rounds found that in Simulation Round 1, DA level participants exhibited superior results in each of the three performance measurements (net income, production delta, repair costs), all four measurements of implicit understanding (demand omission errors, damage omission errors, demand commission error rate, and damage commission error rate), and lower subjective workload for multiple measurements (performance, frustration, composite score). DA level performance and implicit understanding were again significantly higher in Simulation Round 2 for net income, production delta and demand omission errors, but many of the initial gaps in performance, understanding, and workload began to close as the No-DA group improved at a higher rate. Differences between AT levels for repair costs, demand commission error rates, damage omission errors and all subjective workload scores that were significant in round 1 no longer reached significance in round 2. These findings align with previous research that found the presence of automation facilitated initial performance gains but that gap closed with additional training (Clegg et al., 2010).

The results also found that differences between the AT levels in the return-to-manual round were consistent with prior research indicating that RTM performance suffers more with higher levels of automation (Onnasch et al., 2014). The DA group RTM results were significantly worse than round 2 in each of the three performance measurements, each of the four measurements of understanding, and three of the seven subjective workload measurements (performance, frustration, composite score). Interestingly, the No-DA group experienced no significant degradations to performance, workload or understanding between round 2 and the RTM round, and in some instances, improved significantly over round 1 or round 2. Collectively, this indicates the DA group was adversely affected by the reduction in automation experienced in the RTM round, while the impacts to the No-DA group were not significant and in some instances were able to continue to improve over previous rounds. These findings support the claims of Onnasch et al. (2014) that negative consequences of automation are most likely when the degree of automation provided by the automation crosses the critical boundary between information analysis and decision selection.

Despite the significant declines in the DA group's performance, significant differences between AT levels were only identified for two measurements in the RTM round: reaction time and damage commission error rate. The higher reaction times experienced by the DA group in the RTM round suggests that the novel experience of being responsible for control change decisions served to increase workload when automated support was removed. Since performance (net income, production delta, repair costs) did not differ between AT levels the differences in workload appeared insufficient to influence performance.

Results for the damage commission error rate measurement indicated that following nearly identical error rates in round 2, the rates for the DA group participants significantly increased in the RTM round while the No-DA error rate remained relatively unchanged. This suggests that operation of the simulation with decision support inhibited participants' ability to make correct control changes when addressing subsystem damage in the RTM round. A possible explanation for the difference in error rates between AT levels is that DA level participants had less than half the experience (damage omission errors) of their No-DA level counterparts with damaged subsystems, resulting in less time to learn how to correctly address damage. The nuclear power plant simulation provided near real-time feedback and allowed participants to quickly adjust when incorrect control decisions were made, minimizing the impact of incorrect decisions on overall performance. The impacts may be more severe in other dynamic systems where operators have limited opportunity to make correct decisions or the results of single decisions are more impactful. Designers must therefore be cognizant that the use of decision automation may reinforce specific behavioral paths and that operators who rely on their own decision making may choose alternative approaches to managing the system than those suggested by automation. If the use of automation prevents or limits operators from gaining experience managing specific system states and these states are more likely to occur in the event of automation failure, steps must be taken to ensure operators can make correct decisions when these scenarios occur.

These findings begin to answer the first research question, confirming that automation type does influence participants' implicit understanding of a dynamic system. The availability of automated decision support resulted in superior measures of understanding (demand omission errors, demand commission error rate, damage omission error rates), and performance (net income, production delta) but these benefits did not transfer to the RTM round. It also found DA level participants had significantly higher reaction times and damage commission errors in the RTM round; the latter possibly resulting from having less experience controlling the simulation while sub-systems were in a damaged state.

**Display Types**

Differences between Display Types were far less distinct than those between Automation Types, with significant differences identified for only two dependent variables; production delta and frustration. The Semantic-Spatial level participants had a significantly lower production delta and lower frustration scores than those using the Separable display while automated support was available (Simulation Round 1 & 2) and significantly lower frustration scores when all three Simulation Rounds were examined. The addition of explicit feedback pertaining to the causal relationships within the system was the singular difference between the Semantic-Spatial and Separable displays, indicating that the availability of this feedback enhanced performance and reduced frustration. Surprisingly, the differences in production delta and frustration were not accompanied by differences in measures of understanding. The availability of the real-time explanatory feedback failed to improve participants' implicit understanding of the system as none of the understanding measurement results indicated differences between Display Types.

Though evidence was found that differences in Display Types can influence participants' performance and frustration when managing dynamic systems, no evidence was found that Display Types influence implicit understanding. One possible explanation for the lack of findings may be that the highly significant differences between Automation Types introduced such high variance that differences between Display Types were no longer statistically discernable. Differences between individual conditions were investigated to explore this possibility.

**Individual Conditions**

Examination of individual conditions provided additional insight into the results found for the Automation and Display Types. No significant interactions were found between Automation Types and Display Types answering the third research question which sought to understand if the presence of an interaction would influence participants' understanding, but significant differences were found in performance, implicit understanding, and training effects between individual conditions. Evidence was also found that the availability of decision automation may mitigate the differences in Display Types found between the No-DA conditions.

The pronounced differences between AT levels and nominal differences between DT levels in the first two simulation rounds appear to be a result of a distinct division between the DA and No-DA conditions. Participants in the DA conditions consistently surpassed those in the Separable No-DA and Configural No-DA conditions in multiple performance (net income, production delta) and implicit understanding measurements (demand omission errors, demand commission error rate) when automated support was available. Participants in the DA conditions also generally improved at similar rates in round 2 as participants became more familiar with the system and then experienced significant declines in many of the measurements in the RTM round, indicating the benefits decision automation afforded did not transfer. Examination of the RTM round identified differences in participants' damage commission error rates. The Sep:No-DA condition participants were found to have a significantly lower rate than those in the Sep:DA and SS:DA conditions, explaining the significant difference in RTM damage commission error rates found between Automation Types.

Variations in Display Types appeared to have little influence when decision automation was available, as participants in the three DA conditions displayed similar results across many of the performance and understanding measurements in each simulation round. It appears that the availability of decision automation negated differences as variations in display types appeared to have greater influence on these measurements when decision automation was not available. Patterns emerged for each of the three No-DA conditions across demand related measurements of performance and understanding. Participants in the Configural and Semantic No-DA conditions generally began very poorly relative to those in other conditions, exhibiting the lowest Simulation Round 1 performance and implicit understanding scores for nearly all measurements. Unlike the other conditions, participants in the Conf:No-DA and Sep:No-DA conditions exhibited a training effect through the RTM round, significantly improving in many measurements despite the reduction in automated assistance. Though the participants in Conf:No-DA and Sep:No-DA conditions both improved, they appeared to do so at different rates. Differences between conditions did not reach significance, but there were multiple instances in which the Conf:No-DA participants had the highest performance of all conditions in the RTM round (net income, production delta, and demand omission errors) after starting out as the second to worst condition in round 1 while the Sep:No-DA participants started and ended worst of all conditions for net income and performance delta, and ended second worst for demand omission errors. In the instance of production delta, the Conf:No-DA condition participants significantly improved from Simulation Round 1 to round 2, and again from round 2 to the RTM round, while the improvements for the Sep:No-DA condition participants were only significant between the first and RTM rounds. These findings suggest the availability of the configural radar graph allowed participants to improve performance at a greater rate than separable bar graphs, supporting Ayres & Sweller's (2014) claim that the mental integration of disparate sources of information increases extraneous cognitive load and inhibits learning when compared to integrated sources.

Similar results were identified between the Semantic-Spatial No-DA condition and certain aspects of both DA and No-DA conditions. When automated support was available (Simulation Rounds 1 & 2), SS:No-DA participants typically outperformed their two No-DA counterparts and underperformed those in the three DA conditions, but the results were not statistically different from either. The SS:No-DA condition participants experienced declines in the RTM round similarly to those experienced in the DA conditions, but unlike the DA conditions, the declines only reached significance in one instance (demand commission error rate). The availability of explicit feedback within the SS:No-DA condition may have served to offload a degree of the active processing required to manage the system, but not to the extent the availability of full decision automation did. The hybrid like results of the SS:No-DA condition participants suggests that explicit real-time feedback describing the relationships between sub-systems could be an effective middle ground when choosing between different automation and display options. Performance was not significantly different from designs using decision automation in automated simulation rounds, and the significant RTM declines much were less frequent than those experienced in the decision automation conditions.

The absence of significant interactions between Automation and Display Types and minimal differences between Display Types can be explained by the mitigating effect decision automation appears to have on variations in display types. The differences in results between no decision automation conditions were simply insufficient to offset the consistency in results observed between decision automation conditions. The identification of this mitigating effect, the differences in training effect between the participants in Sep:No-DA and Conf:No-DA conditions, and the hybrid characteristics of the SS:No-DA condition results each provide novel insight into how display and automation designs influence operators ability to manage dynamic systems.

### Explicit Understanding

Investigation of how different Automation and Display types influenced participants' explicit understanding of a dynamic system failed to identify differences between conditions or factors. Especially surprising was that the explicit feedback provided in the Semantic-Spatial Display Type failed to improve participants performance on the assessment, despite providing real-time insight into the relationships between individual subsystems and between subsystems and controls. Prior research may explain why differences in explicit knowledge were not found. Broadbent et al. (1986) found that practicing the total task does not improve the ability to answer questions about it, but practicing isolated relationships does. Though the explicit feedback provided in the Semantic-Spatial display pertained to isolated relationships within the system, participants were still managing the total task. The results provide evidence to corroborate and extend Broadbent's findings, suggesting that real-time explicit feedback about isolated relationships within a dynamic system does not improve explicit knowledge when participants are performing total tasks.

### Explicit and Implicit Understanding's Influence on Return-to-Manual Performance

Examination of the stepwise regression results revealed both expected and unanticipated relationships between Simulation Round 1 and 2 workload and explicit and implicit understanding measurements with the RTM Deltas for repair costs, production delta, and net income. Three distinct associations become apparent when examining the results for net income. The first is that higher assessment scores predicted smaller RTM Deltas for the DA and total populations, indicating that a better explicit understanding of the simulation provided an insulating effect to the negative performance impacts experienced when automated assistance is removed. Three of the six models (DA, Conf, SS) identified higher levels of workload (subjective and reaction times) as predictors of larger RTM Deltas. This suggests that participants who found the simulation to be more difficult, effortful, or demanding when automated assistance was available experienced greater declines in performance in the RTM round. Each of the six regression models identified either higher demand omission errors or a higher demand commission error rate as predictors of smaller RTM Deltas. This counterintuitive finding indicates that a poorer implicit understanding of the system in Simulation Round 1 & 2 predicted better performance in the RTM round relative to round 2. A possible explanation may lie with how people develop mental models of dynamic systems. Chi et al. (1994) identified three types of knowledge required to understand a physical system: a knowledge of the physical configuration of the system and its components, a knowledge of the behavior of the machine and how the components interact and affect each other, and an understanding the overall function and purpose of the system (Hegarty, 2014). The physical layout and the function of the system were provided to the user through the video tutorial of the simulation and through each display, leaving the development of an understanding of the behavior of the system to be developed through direct interaction. Participants operating with the aid of decision support or explicit feedback may have received less corrective feedback, experiencing primarily positive outcome feedback which affirmed their decisions. Thus, participants that had lower demand commission error rates and lower omission error counts had less opportunity to observe the behavior of the system when it was in a state of error and were unable to develop a mental model that accurately represented the behavior of the system in this state. When automated assistance was reduced and the system entered a state of error, the participant may not have developed an adequate understanding of the behavior of the system to make the appropriate corrections.

Net income was a composite measurement primarily comprised of production delta and repair costs. The contributions of each were dependent upon participant performance, but production delta typically composed the majority of net income. Unsurprisingly, the production delta regression models were similar to net income, with lower workload and higher round 1 demand omission errors and demand commission error rates predicting smaller RTM Deltas. An exception was found for workload, with higher round 1 physical workload scores predicting lower RTM deltas for DA level participants. A possible explanation for this may be that those participants in the DA level who found the first simulation round more physically challenging may have been less reliant on the decision automation and which better prepared them for the loss of automated assistance in the RTM round.

The regression models for repair costs identified higher assessment scores predicted smaller RTM Deltas in the DA and total populations, and likely contributed to the identical findings for net income. In addition, higher demand and damage omission errors, and demand commission error rates predicted lower RTM deltas with the exception of higher round 1 damage omission errors for the total population. The contribution of round 1 damage omission errors to the model was relatively low and the lack of supporting data make the interpretation of these results speculative.

The results of the regression analysis provide evidence that measurements of workload and explicit and implicit understanding have predictive value when evaluating the impact that the loss of automated support will have on performance. This extends previous research on both the role of explicit and implicit understanding's influence on the management of dynamic systems and the contributing factors that influence the degradation of performance in return-to-manual scenarios.

## Conclusion

The results of this experiment support a number of prior claims and extend our understanding of how automation and display types influence dynamic system management in multiple areas. The most notable advancements include the findings that decision automation appears to minimize the differences display types have on novice-level participants' performance, workload, and understanding, where distinct differences are found between conditions without decision automation. These differences include the influence displays have on the rate at which participants' performance improves, and the identification of a hybrid condition which exhibits positive characteristics found within other conditions. In addition, the presence of explicit real-time feedback has shown to improve performance and reduce frustration but does nothing to improve participants' explicit understanding of the rules and relationships that govern the simulation. Improvements in participants' explicit understanding, lower workload and higher implicit errors are shown to predict improved resilience to the negative impacts return-to-manual scenarios have on performance. Finally, operation of the system with the aid of decision automation results in higher error rates in return-to-manual scenarios when the system is in a damaged state. The most plausible explanation for this finding is that operation with decision automation results in considerably less experience interacting with the system in a damaged state. Participants perhaps simply never gain the experience necessary to learn how to appropriately control the system in that state.

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## Appendix A

NASA TLX

Mental Demand How mentally demanding was the task?

Very Low Very High

Physical Demand How physically demanding was the task?

Very Low Very High

Temporal Demand How hurried or rushed was the pace of the task?

Very Low Very High

Performance How successful were you in accomplishing what you were asked to do?

Perfect Failure

Effort How hard did you have to work to accomplish your level of performance?

Very Low Very High

Frustration How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low Very High

## Appendix B

*Nuclear Power Simulation Assessment*

The following questions pertain to the relationships between the adjustments made to the controls and the effect on the sub-systems within the Nuclear Power Plant.

1. To increase the temperature of the Reactor Core the following control adjustment(s) can be made (please select all that apply):
    a. Increase the Reactor Core Control
    b. Increase the Primary Coolant Pump Control
    c. Increase the Secondary Coolant Pump Control
    d. Decrease the Reactor Core Control
    e. Decrease the Primary Coolant Pump Control
    f. Decrease the Secondary Coolant Pump Control

2. To increase the Primary Coolant Pump speed the following control adjustment(s) can be made (please select all that apply):
    a. Increase the Reactor Core Control
    b. Increase the Primary Coolant Pump Control
    c. Increase the Secondary Coolant Pump Control
    d. Decrease the Reactor Core Control
    e. Decrease the Primary Coolant Pump Control
    f. Decrease the Secondary Coolant Pump Control

3. To increase the Heat Exchanger temperature the following control adjustment(s) can be made (please select all that apply):
    a. Increase the Reactor Core Control
    b. Increase the Primary Coolant Pump Control
    c. Increase the Secondary Coolant Pump Control
    d. Decrease the Reactor Core Control
    e. Decrease the Primary Coolant Pump Control
    f. Decrease the Secondary Coolant Pump Control

4. To stop emergency venting from continuing to vent, the following control adjustment(s) can be made (please select all that apply):
    a. Increase the Reactor Core Control
    b. Increase the Primary Coolant Pump Control
    c. Increase the Secondary Coolant Pump Control
    d. Decrease the Reactor Core Control
    e. Decrease the Primary Coolant Pump Control
    f. Decrease the Secondary Coolant Pump Control

5. To increase the Steam Turbine speed the following control adjustment(s) can be made (please select all that apply):
    a. Increase the Reactor Core Control
    b. Increase the Primary Coolant Pump Control
    c. Increase the Secondary Coolant Pump Control
    d. Decrease the Reactor Core Control
    e. Decrease the Primary Coolant Pump Control
    f. Decrease the Secondary Coolant Pump Control

6. To increase the AC Generator speed the following control adjustment(s) can be made (please select all that apply):
    a. Increase the Reactor Core Control
    b. Increase the Primary Coolant Pump Control
    c. Increase the Secondary Coolant Pump Control
    d. Decrease the Reactor Core Control
    e. Decrease the Primary Coolant Pump Control
    f. Decrease the Secondary Coolant Pump Control

7. To increase the Cooling Tower temperature the following control adjustment(s) can be made (please select all that apply):
    a. Increase the Reactor Core Control
    b. Increase the Primary Coolant Pump Control
    c. Increase the Secondary Coolant Pump Control
    d. Decrease the Reactor Core Control
    e. Decrease the Primary Coolant Pump Control
    f. Decrease the Secondary Coolant Pump Control

8. To increase the Secondary Cooling Pump speed the following control adjustment(s) can be made (please select all that apply):
    a. Increase the Reactor Core Control
    b. Increase the Primary Coolant Pump Control
    c. Increase the Secondary Coolant Pump Control
    d. Decrease the Reactor Core Control
    e. Decrease the Primary Coolant Pump Control
    f. Decrease the Secondary Coolant Pump Control

The following questions pertain to the relationships between the sub-systems within the Nuclear Power Plant.

9. If the Reactor Core temperature increases the Primary Coolant Pump speed will:
    a. Increase

   b. Decrease
   c. Remain Unchanged

10. If the Primary Coolant Pump speed increases, the Heat Exchanger temperature will:
    a. Increase
    b. Decrease
    c. Remain Unchanged

11. If the Heat Exchanger temperature increases, the Emergency Venting will:
    a. Increase
    b. Decrease
    c. Remain Unchanged

12. If the Heat Exchanger temperature increases, the Steam Turbine speed will:
    a. Increase
    b. Decrease
    c. Remain Unchanged

13. If the Steam Turbine speed increases, the AC Generator speed will:
    a. Increase
    b. Decrease
    c. Remain Unchanged

14. If the Steam Turbine speed increases, the Cooling Tower temperature will:
    a. Increase
    b. Decrease
    c. Remain Unchanged

15. If the Cooling Tower temperature increases, the Secondary Coolant Pump speed will:
    a. Increase
    b. Decrease
    c. Remain Unchanged

16. If the Secondary Coolant Pump speed increases, the Heat Exchanger temperature will:
    a. Increase
    b. Decrease
    c. Remain Unchanged

## Appendix C

Table C-1

*Net Income Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 6543262.00 | 1512053.489 | 15 |
| | | Sep | 5866532.00 | 2125249.094 | 15 |
| | | SS | 6092798.00 | 2148691.679 | 15 |
| | | Total | 6167530.67 | 1927306.785 | 45 |
| | No-DA | Conf | 3747090.00 | 1967254.436 | 15 |
| | | Sep | 3506884.00 | 2012671.554 | 15 |
| | | SS | 5098876.00 | 2169802.364 | 15 |
| | | Total | 4117616.67 | 2126152.210 | 45 |
| | Total | Conf | 5145176.00 | 2234748.113 | 30 |
| | | Sep | 4686708.00 | 2361362.604 | 30 |
| | | SS | 5595837.00 | 2181094.017 | 30 |
| | | Total | 5142573.67 | 2265743.527 | 90 |
| Round 2 | DA | Conf | 7452782.00 | 1011947.242 | 15 |
| | | Sep | 6838006.00 | 1495690.277 | 15 |
| | | SS | 7188944.00 | 1420819.483 | 15 |
| | | Total | 7159910.67 | 1320911.809 | 45 |
| | No-DA | Conf | 5510290.00 | 2471201.184 | 15 |
| | | Sep | 4217172.00 | 2967843.631 | 15 |
| | | SS | 6312618.00 | 2281136.872 | 15 |
| | | Total | 5346693.33 | 2676467.835 | 45 |
| | Total | Conf | 6481536.00 | 2101984.111 | 30 |
| | | Sep | 5527589.00 | 2666189.161 | 30 |
| | | SS | 6750781.00 | 1919698.185 | 30 |
| | | Total | 6253302.00 | 2288071.683 | 90 |
| Round 3 | DA | Conf | 6196214.00 | 2005025.867 | 15 |
| | | Sep | 5675256.00 | 1651047.695 | 15 |
| | | SS | 6052210.00 | 1336449.459 | 15 |
| | | Total | 5974560.00 | 1662567.324 | 45 |
| | No-DA | Conf | 6473884.00 | 1614717.756 | 15 |
| | | Sep | 4981684.00 | 2670396.480 | 15 |
| | | SS | 5762848.00 | 1831387.757 | 15 |
| | | Total | 5739472.00 | 2132031.777 | 45 |
| | Total | Conf | 6335049.00 | 1794267.163 | 30 |
| | | Sep | 5328470.00 | 2209739.240 | 30 |
| | | SS | 5907529.00 | 1582109.826 | 30 |
| | | Total | 5857016.00 | 1904665.578 | 90 |

Table C-2

*Net Income Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 6543262.00 | 1512053.489 | 15 |
| | Conf:No-DA | 3747090.00 | 1967254.436 | 15 |
| | Sep:DA | 5866532.00 | 2125249.094 | 15 |
| | Sep:No-DA | 3506884.00 | 2012671.554 | 15 |
| | SS:DA | 6092798.00 | 2148691.679 | 15 |
| | SS:No-DA | 5098876.00 | 2169802.364 | 15 |
| | Total | 5142573.67 | 2265743.527 | 90 |
| Round 2 | Conf:DA | 7452782.00 | 1011947.242 | 15 |
| | Conf:No-DA | 5510290.00 | 2471201.184 | 15 |
| | Sep:DA | 6838006.00 | 1495690.277 | 15 |
| | Sep:No-DA | 4217172.00 | 2967843.631 | 15 |
| | SS:DA | 7188944.00 | 1420819.483 | 15 |
| | SS:No-DA | 6312618.00 | 2281136.872 | 15 |
| | Total | 6253302.00 | 2288071.683 | 90 |
| Round 3 | Conf:DA | 6196214.00 | 2005025.867 | 15 |
| | Conf:No-DA | 6473884.00 | 1614717.756 | 15 |
| | Sep:DA | 5675256.00 | 1651047.695 | 15 |
| | Sep:No-DA | 4981684.00 | 2670396.480 | 15 |
| | SS:DA | 6052210.00 | 1336449.459 | 15 |
| | SS:No-DA | 5762848.00 | 1831387.757 | 15 |
| | Total | 5857016.00 | 1904665.578 | 90 |

Table C-3

*Production Delta Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 24.27 | 15.234 | 15 |
| | | Sep | 31.13 | 20.622 | 15 |
| | | SS | 28.27 | 21.076 | 15 |
| | | Total | 27.89 | 18.937 | 45 |
| | No-DA | Conf | 50.80 | 21.631 | 15 |
| | | Sep | 54.00 | 21.125 | 15 |
| | | SS | 35.93 | 20.957 | 15 |
| | | Total | 46.91 | 22.226 | 45 |
| | Total | Conf | 37.53 | 22.803 | 30 |
| | | Sep | 42.57 | 23.579 | 30 |
| | | SS | 32.10 | 21.016 | 30 |
| | | Total | 37.40 | 22.649 | 90 |
| Round 2 | DA | Conf | 15.53 | 9.978 | 15 |
| | | Sep | 21.47 | 14.990 | 15 |
| | | SS | 16.67 | 12.500 | 15 |
| | | Total | 17.89 | 12.635 | 45 |
| | No-DA | Conf | 33.53 | 25.903 | 15 |
| | | Sep | 46.60 | 31.541 | 15 |
| | | SS | 23.60 | 20.725 | 15 |
| | | Total | 34.58 | 27.521 | 45 |
| | Total | Conf | 24.53 | 21.349 | 30 |
| | | Sep | 34.03 | 27.424 | 30 |
| | | SS | 20.13 | 17.182 | 30 |
| | | Total | 26.23 | 22.887 | 90 |
| Round 3 | DA | Conf | 25.00 | 20.557 | 15 |
| | | Sep | 27.67 | 16.456 | 15 |
| | | SS | 23.73 | 13.525 | 15 |
| | | Total | 25.47 | 16.780 | 45 |
| | No-DA | Conf | 23.33 | 16.706 | 15 |
| | | Sep | 37.73 | 29.285 | 15 |
| | | SS | 26.27 | 16.615 | 15 |
| | | Total | 29.11 | 22.114 | 45 |
| | Total | Conf | 24.17 | 18.424 | 30 |
| | | Sep | 32.70 | 23.895 | 30 |
| | | SS | 25.00 | 14.941 | 30 |
| | | Total | 27.29 | 19.604 | 90 |

Table C-4

*Production Delta Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 24.27 | 15.234 | 15 |
| | Conf:No-DA | 50.80 | 21.631 | 15 |
| | Sep:DA | 31.13 | 20.622 | 15 |
| | Sep:No-DA | 54.00 | 21.125 | 15 |
| | SS:DA | 28.27 | 21.076 | 15 |
| | SS:No-DA | 35.93 | 20.957 | 15 |
| | Total | 37.40 | 22.649 | 90 |
| Round 2 | Conf:DA | 15.53 | 9.978 | 15 |
| | Conf:No-DA | 33.53 | 25.903 | 15 |
| | Sep:DA | 21.47 | 14.990 | 15 |
| | Sep:No-DA | 46.60 | 31.541 | 15 |
| | SS:DA | 16.67 | 12.500 | 15 |
| | SS:No-DA | 23.60 | 20.725 | 15 |
| | Total | 26.23 | 22.887 | 90 |
| Round 3 | Conf:DA | 25.00 | 20.557 | 15 |
| | Conf:No-DA | 23.33 | 16.706 | 15 |
| | Sep:DA | 27.67 | 16.456 | 15 |
| | Sep:No-DA | 37.73 | 29.285 | 15 |
| | SS:DA | 23.73 | 13.525 | 15 |
| | SS:No-DA | 26.27 | 16.615 | 15 |
| | Total | 27.29 | 19.604 | 90 |

Table C-5

*Repair Costs Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 105350.00 | 159598.738 | 15 |
| | | Sep | 104050.00 | 121849.849 | 15 |
| | | SS | 157600.00 | 313574.820 | 15 |
| | | Total | 122333.33 | 211545.886 | 45 |
| | No-DA | Conf | 279150.00 | 369362.431 | 15 |
| | | Sep | 187550.00 | 254057.207 | 15 |
| | | SS | 394550.00 | 480563.380 | 15 |
| | | Total | 287083.33 | 380477.907 | 45 |
| | Total | Conf | 192250.00 | 293207.786 | 30 |
| | | Sep | 145800.00 | 200326.128 | 30 |
| | | SS | 276075.00 | 416507.416 | 30 |
| | | Total | 204708.33 | 317103.677 | 90 |
| Round 2 | DA | Conf | 60100.00 | 132346.501 | 15 |
| | | Sep | 90200.00 | 141790.659 | 15 |
| | | SS | 208600.00 | 665007.759 | 15 |
| | | Total | 119633.33 | 396084.851 | 45 |
| | No-DA | Conf | 215150.00 | 528117.164 | 15 |
| | | Sep | 233100.00 | 509845.581 | 15 |
| | | SS | 413700.00 | 877868.366 | 15 |
| | | Total | 287316.67 | 651830.413 | 45 |
| | Total | Conf | 137625.00 | 386417.251 | 30 |
| | | Sep | 161650.00 | 374801.675 | 30 |
| | | SS | 311150.00 | 772276.744 | 30 |
| | | Total | 203475.00 | 542884.064 | 90 |
| Round 3 | DA | Conf | 378400.00 | 538893.872 | 15 |
| | | Sep | 636900.00 | 499444.672 | 15 |
| | | SS | 649550.00 | 801826.142 | 15 |
| | | Total | 554950.00 | 626342.149 | 45 |
| | No-DA | Conf | 267050.00 | 513052.117 | 15 |
| | | Sep | 334100.00 | 681835.619 | 15 |
| | | SS | 687800.00 | 924018.109 | 15 |
| | | Total | 429650.00 | 733611.773 | 45 |
| | Total | Conf | 322725.00 | 520072.883 | 30 |
| | | Sep | 485500.00 | 607098.409 | 30 |
| | | SS | 668675.00 | 850258.739 | 30 |
| | | Total | 492300.00 | 681165.919 | 90 |

Table C-6

*Repair Costs Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 105350.00 | 159598.738 | 15 |
| | Conf:No-DA | 279150.00 | 369362.431 | 15 |
| | Sep:DA | 104050.00 | 121849.849 | 15 |
| | Sep:No-DA | 187550.00 | 254057.207 | 15 |
| | SS:DA | 157600.00 | 313574.820 | 15 |
| | SS:No-DA | 394550.00 | 480563.380 | 15 |
| | Total | 204708.33 | 317103.677 | 90 |
| Round 2 | Conf:DA | 60100.00 | 132346.501 | 15 |
| | Conf:No-DA | 215150.00 | 528117.164 | 15 |
| | Sep:DA | 90200.00 | 141790.659 | 15 |
| | Sep:No-DA | 233100.00 | 509845.581 | 15 |
| | SS:DA | 208600.00 | 665007.759 | 15 |
| | SS:No-DA | 413700.00 | 877868.366 | 15 |
| | Total | 203475.00 | 542884.064 | 90 |
| Round 3 | Conf:DA | 378400.00 | 538893.872 | 15 |
| | Conf:No-DA | 267050.00 | 513052.117 | 15 |
| | Sep:DA | 636900.00 | 499444.672 | 15 |
| | Sep:No-DA | 334100.00 | 681835.619 | 15 |
| | SS:DA | 649550.00 | 801826.142 | 15 |
| | SS:No-DA | 687800.00 | 924018.109 | 15 |
| | Total | 492300.00 | 681165.919 | 90 |

Table C-7

*Demand Omission Errors Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 108.73 | 108.927 | 15 |
| | | Sep | 148.47 | 147.000 | 15 |
| | | SS | 129.47 | 167.740 | 15 |
| | | Total | 128.89 | 140.971 | 45 |
| | No-DA | Conf | 328.60 | 156.011 | 15 |
| | | Sep | 349.73 | 219.557 | 15 |
| | | SS | 217.40 | 146.427 | 15 |
| | | Total | 298.58 | 182.621 | 45 |
| | Total | Conf | 218.67 | 173.148 | 30 |
| | | Sep | 249.10 | 210.189 | 30 |
| | | SS | 173.43 | 161.039 | 30 |
| | | Total | 213.73 | 183.281 | 90 |
| Round 2 | DA | Conf | 60.13 | 76.975 | 15 |
| | | Sep | 99.33 | 112.288 | 15 |
| | | SS | 60.67 | 87.656 | 15 |
| | | Total | 73.38 | 93.201 | 45 |
| | No-DA | Conf | 235.67 | 175.904 | 15 |
| | | Sep | 249.80 | 184.812 | 15 |
| | | SS | 110.47 | 118.502 | 15 |
| | | Total | 198.64 | 170.854 | 45 |
| | Total | Conf | 147.90 | 160.520 | 30 |
| | | Sep | 174.57 | 168.615 | 30 |
| | | SS | 85.57 | 105.498 | 30 |
| | | Total | 136.01 | 150.642 | 90 |
| Round 3 | DA | Conf | 182.60 | 169.335 | 15 |
| | | Sep | 241.13 | 125.733 | 15 |
| | | SS | 191.20 | 122.194 | 15 |
| | | Total | 204.98 | 139.949 | 45 |
| | No-DA | Conf | 146.93 | 95.626 | 15 |
| | | Sep | 214.33 | 186.284 | 15 |
| | | SS | 197.87 | 133.247 | 15 |
| | | Total | 186.38 | 142.976 | 45 |
| | Total | Conf | 164.77 | 136.332 | 30 |
| | | Sep | 227.73 | 156.748 | 30 |
| | | SS | 194.53 | 125.663 | 30 |
| | | Total | 195.68 | 140.984 | 90 |

Table C-8

*Demand Omission Errors Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 108.73 | 108.927 | 15 |
| | Conf:No-DA | 328.60 | 156.011 | 15 |
| | Sep:DA | 148.47 | 147.000 | 15 |
| | Sep:No-DA | 349.73 | 219.557 | 15 |
| | SS:DA | 129.47 | 167.740 | 15 |
| | SS:No-DA | 217.40 | 146.427 | 15 |
| | Total | 213.73 | 183.281 | 90 |
| Round 2 | Conf:DA | 60.13 | 76.975 | 15 |
| | Conf:No-DA | 235.67 | 175.904 | 15 |
| | Sep:DA | 99.33 | 112.288 | 15 |
| | Sep:No-DA | 249.80 | 184.812 | 15 |
| | SS:DA | 60.67 | 87.656 | 15 |
| | SS:No-DA | 110.47 | 118.502 | 15 |
| | Total | 136.01 | 150.642 | 90 |
| Round 3 | Conf:DA | 182.60 | 169.335 | 15 |
| | Conf:No-DA | 146.93 | 95.626 | 15 |
| | Sep:DA | 241.13 | 125.733 | 15 |
| | Sep:No-DA | 214.33 | 186.284 | 15 |
| | SS:DA | 191.20 | 122.194 | 15 |
| | SS:No-DA | 197.87 | 133.247 | 15 |
| | Total | 195.68 | 140.984 | 90 |

Table C-9

*Demand Commission Error Rate Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 0.1206 | 0.05644 | 15 |
| | | Sep | 0.1476 | 0.06393 | 15 |
| | | SS | 0.1210 | 0.06047 | 15 |
| | | Total | 0.1297 | 0.06033 | 45 |
| | No-DA | Conf | 0.2236 | 0.05196 | 15 |
| | | Sep | 0.2442 | 0.08569 | 15 |
| | | SS | 0.1960 | 0.05861 | 15 |
| | | Total | 0.2213 | 0.06845 | 45 |
| | Total | Conf | 0.1721 | 0.07473 | 30 |
| | | Sep | 0.1959 | 0.08906 | 30 |
| | | SS | 0.1585 | 0.06986 | 30 |
| | | Total | 0.1755 | 0.07896 | 90 |
| Round 2 | DA | Conf | 0.1400 | 0.06275 | 15 |
| | | Sep | 0.1320 | 0.07560 | 15 |
| | | SS | 0.1195 | 0.06995 | 15 |
| | | Total | 0.1305 | 0.06857 | 45 |
| | No-DA | Conf | 0.1964 | 0.08263 | 15 |
| | | Sep | 0.1729 | 0.07620 | 15 |
| | | SS | 0.1299 | 0.04543 | 15 |
| | | Total | 0.1664 | 0.07384 | 45 |
| | Total | Conf | 0.1682 | 0.07757 | 30 |
| | | Sep | 0.1524 | 0.07742 | 30 |
| | | SS | 0.1247 | 0.05819 | 30 |
| | | Total | 0.1484 | 0.07311 | 90 |
| Round 3 | DA | Conf | 0.1845 | 0.08455 | 15 |
| | | Sep | 0.1971 | 0.07344 | 15 |
| | | SS | 0.1835 | 0.07854 | 15 |
| | | Total | 0.1884 | 0.07741 | 45 |
| | No-DA | Conf | 0.1492 | 0.07292 | 15 |
| | | Sep | 0.1763 | 0.08089 | 15 |
| | | SS | 0.1890 | 0.09913 | 15 |
| | | Total | 0.1715 | 0.08475 | 45 |
| | Total | Conf | 0.1669 | 0.07962 | 30 |
| | | Sep | 0.1867 | 0.07665 | 30 |
| | | SS | 0.1863 | 0.08792 | 30 |
| | | Total | 0.1799 | 0.08115 | 90 |

Table C-10

*Demand Commission Error Rate Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 0.1206 | 0.05644 | 15 |
| | Conf:No-DA | 0.2236 | 0.05196 | 15 |
| | Sep:DA | 0.1476 | 0.06393 | 15 |
| | Sep:No-DA | 0.2442 | 0.08569 | 15 |
| | SS:DA | 0.1210 | 0.06047 | 15 |
| | SS:No-DA | 0.1960 | 0.05861 | 15 |
| | Total | 0.1755 | 0.07896 | 90 |
| Round 2 | Conf:DA | 0.1400 | 0.06275 | 15 |
| | Conf:No-DA | 0.1964 | 0.08263 | 15 |
| | Sep:DA | 0.1320 | 0.07560 | 15 |
| | Sep:No-DA | 0.1729 | 0.07620 | 15 |
| | SS:DA | 0.1195 | 0.06995 | 15 |
| | SS:No-DA | 0.1299 | 0.04543 | 15 |
| | Total | 0.1484 | 0.07311 | 90 |
| Round 3 | Conf:DA | 0.1845 | 0.08455 | 15 |
| | Conf:No-DA | 0.1492 | 0.07292 | 15 |
| | Sep:DA | 0.1971 | 0.07344 | 15 |
| | Sep:No-DA | 0.1763 | 0.08089 | 15 |
| | SS:DA | 0.1835 | 0.07854 | 15 |
| | SS:No-DA | 0.1890 | 0.09913 | 15 |
| | Total | 0.1799 | 0.08115 | 90 |

Table C-11

*Damage Omission Errors Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 34.33 | 51.271 | 15 |
| | | Sep | 32.00 | 40.463 | 15 |
| | | SS | 61.13 | 138.654 | 15 |
| | | Total | 42.49 | 87.482 | 45 |
| | No-DA | Conf | 109.87 | 129.048 | 15 |
| | | Sep | 87.27 | 132.121 | 15 |
| | | SS | 145.13 | 149.820 | 15 |
| | | Total | 114.09 | 136.289 | 45 |
| | Total | Conf | 72.10 | 103.846 | 30 |
| | | Sep | 59.63 | 100.037 | 30 |
| | | SS | 103.13 | 148.128 | 30 |
| | | Total | 78.29 | 119.426 | 90 |
| Round 2 | DA | Conf | 34.27 | 86.953 | 15 |
| | | Sep | 33.00 | 44.913 | 15 |
| | | SS | 65.67 | 211.130 | 15 |
| | | Total | 44.31 | 132.152 | 45 |
| | No-DA | Conf | 72.67 | 140.377 | 15 |
| | | Sep | 83.53 | 150.910 | 15 |
| | | SS | 154.80 | 297.399 | 15 |
| | | Total | 103.67 | 207.402 | 45 |
| | Total | Conf | 53.47 | 116.381 | 30 |
| | | Sep | 58.27 | 112.377 | 30 |
| | | SS | 110.23 | 257.434 | 30 |
| | | Total | 73.99 | 175.473 | 90 |
| Round 3 | DA | Conf | 150.20 | 162.311 | 15 |
| | | Sep | 241.13 | 157.125 | 15 |
| | | SS | 234.87 | 239.834 | 15 |
| | | Total | 208.73 | 190.521 | 45 |
| | No-DA | Conf | 134.73 | 243.839 | 15 |
| | | Sep | 122.33 | 233.725 | 15 |
| | | SS | 230.80 | 243.336 | 15 |
| | | Total | 162.62 | 239.881 | 45 |
| | Total | Conf | 142.47 | 203.675 | 30 |
| | | Sep | 181.73 | 204.793 | 30 |
| | | SS | 232.83 | 237.398 | 30 |
| | | Total | 185.68 | 216.636 | 90 |

Table C-12

*Damage Omission Error Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 34.33 | 51.271 | 15 |
| | Conf:No-DA | 109.87 | 129.048 | 15 |
| | Sep:DA | 32.00 | 40.463 | 15 |
| | Sep:No-DA | 87.27 | 132.121 | 15 |
| | SS:DA | 61.13 | 138.654 | 15 |
| | SS:No-DA | 145.13 | 149.820 | 15 |
| | Total | 78.29 | 119.426 | 90 |
| Round 2 | Conf:DA | 34.27 | 86.953 | 15 |
| | Conf:No-DA | 72.67 | 140.377 | 15 |
| | Sep:DA | 33.00 | 44.913 | 15 |
| | Sep:No-DA | 83.53 | 150.910 | 15 |
| | SS:DA | 65.67 | 211.130 | 15 |
| | SS:No-DA | 154.80 | 297.399 | 15 |
| | Total | 73.99 | 175.473 | 90 |
| Round 3 | Conf:DA | 150.20 | 162.311 | 15 |
| | Conf:No-DA | 134.73 | 243.839 | 15 |
| | Sep:DA | 241.13 | 157.125 | 15 |
| | Sep:No-DA | 122.33 | 233.725 | 15 |
| | SS:DA | 234.87 | 239.834 | 15 |
| | SS:No-DA | 230.80 | 243.336 | 15 |
| | Total | 185.68 | 216.636 | 90 |

Table C-13

*Damage Commission Error Rate Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 0.0989 | 0.09957 | 15 |
| | | Sep | 0.1248 | 0.10666 | 15 |
| | | SS | 0.1003 | 0.13374 | 15 |
| | | Total | 0.1080 | 0.11230 | 45 |
| | No-DA | Conf | 0.1515 | 0.09114 | 15 |
| | | Sep | 0.1268 | 0.11552 | 15 |
| | | SS | 0.1530 | 0.11056 | 15 |
| | | Total | 0.1438 | 0.10453 | 45 |
| | Total | Conf | 0.1252 | 0.09753 | 30 |
| | | Sep | 0.1258 | 0.10925 | 30 |
| | | SS | 0.1266 | 0.12351 | 30 |
| | | Total | 0.1259 | 0.10936 | 90 |
| Round 2 | DA | Conf | 0.0658 | 0.09332 | 15 |
| | | Sep | 0.0925 | 0.09643 | 15 |
| | | SS | 0.0941 | 0.13477 | 15 |
| | | Total | 0.0841 | 0.10808 | 45 |
| | No-DA | Conf | 0.0985 | 0.07290 | 15 |
| | | Sep | 0.0973 | 0.08391 | 15 |
| | | SS | 0.0618 | 0.09039 | 15 |
| | | Total | 0.0859 | 0.08263 | 45 |
| | Total | Conf | 0.0822 | 0.08394 | 30 |
| | | Sep | 0.0949 | 0.08885 | 30 |
| | | SS | 0.0779 | 0.11394 | 30 |
| | | Total | 0.0850 | 0.09566 | 90 |
| Round 3 | DA | Conf | 0.1829 | 0.12836 | 15 |
| | | Sep | 0.2028 | 0.06857 | 15 |
| | | SS | 0.1844 | 0.13619 | 15 |
| | | Total | 0.1900 | 0.11280 | 45 |
| | No-DA | Conf | 0.1133 | 0.09106 | 15 |
| | | Sep | 0.0648 | 0.09676 | 15 |
| | | SS | 0.1001 | 0.11261 | 15 |
| | | Total | 0.0927 | 0.10041 | 45 |
| | Total | Conf | 0.1481 | 0.11493 | 30 |
| | | Sep | 0.1338 | 0.10826 | 30 |
| | | SS | 0.1422 | 0.13006 | 30 |
| | | Total | 0.1414 | 0.11692 | 90 |

Table C-14

*Damage Commission Error Rate Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 0.0989 | 0.09957 | 15 |
| | Conf:No-DA | 0.1515 | 0.09114 | 15 |
| | Sep:DA | 0.1248 | 0.10666 | 15 |
| | Sep:No-DA | 0.1268 | 0.11552 | 15 |
| | SS:DA | 0.1003 | 0.13374 | 15 |
| | SS:No-DA | 0.1530 | 0.11056 | 15 |
| | Total | 0.1259 | 0.10936 | 90 |
| Round 2 | Conf:DA | 0.0658 | 0.09332 | 15 |
| | Conf:No-DA | 0.0985 | 0.07290 | 15 |
| | Sep:DA | 0.0925 | 0.09643 | 15 |
| | Sep:No-DA | 0.0973 | 0.08391 | 15 |
| | SS:DA | 0.0941 | 0.13477 | 15 |
| | SS:No-DA | 0.0618 | 0.09039 | 15 |
| | Total | 0.0850 | 0.09566 | 90 |
| Round 3 | Conf:DA | 0.1829 | 0.12836 | 15 |
| | Conf:No-DA | 0.1133 | 0.09106 | 15 |
| | Sep:DA | 0.2028 | 0.06857 | 15 |
| | Sep:No-DA | 0.0648 | 0.09676 | 15 |
| | SS:DA | 0.1844 | 0.13619 | 15 |
| | SS:No-DA | 0.1001 | 0.11261 | 15 |
| | Total | 0.1414 | 0.11692 | 90 |

Table C-15

*Assessment Score Descriptive Statistics by Automation Type and Display Type*

| Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|
| DA | Conf | 3.07 | 5.910 | 15 |
| | Sep | -1.40 | 7.268 | 15 |
| | SS | -2.47 | 6.823 | 15 |
| | Total | -0.27 | 6.972 | 45 |
| No-DA | Conf | 0.93 | 4.713 | 15 |
| | Sep | 2.47 | 5.330 | 15 |
| | SS | 0.47 | 5.012 | 15 |
| | Total | 1.29 | 4.985 | 45 |
| Total | Conf | 2.00 | 5.363 | 30 |
| | Sep | 0.53 | 6.564 | 30 |
| | SS | -1.00 | 6.069 | 30 |
| | Total | 0.51 | 6.077 | 90 |

Table C-16

*Reaction Time Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 9.3284 | 4.80274 | 15 |
| | | Sep | 12.1847 | 7.84598 | 15 |
| | | SS | 7.6408 | 8.49302 | 15 |
| | | Total | 9.7179 | 7.31261 | 45 |
| | No-DA | Conf | 6.3637 | 4.12231 | 15 |
| | | Sep | 9.1321 | 4.51744 | 15 |
| | | SS | 7.1880 | 5.21545 | 15 |
| | | Total | 7.5613 | 4.68324 | 45 |
| | Total | Conf | 7.8460 | 4.64891 | 30 |
| | | Sep | 10.6584 | 6.47919 | 30 |
| | | SS | 7.4144 | 6.92868 | 30 |
| | | Total | 8.6396 | 6.20127 | 90 |
| Round 2 | DA | Conf | 6.9306 | 4.71280 | 15 |
| | | Sep | 9.4293 | 6.70992 | 15 |
| | | SS | 7.6625 | 7.87949 | 15 |
| | | Total | 8.0075 | 6.50171 | 45 |
| | No-DA | Conf | 5.5680 | 5.55760 | 15 |
| | | Sep | 6.2985 | 3.83573 | 15 |
| | | SS | 6.2048 | 5.25212 | 15 |
| | | Total | 6.0238 | 4.83670 | 45 |
| | Total | Conf | 6.2493 | 5.11013 | 30 |
| | | Sep | 7.8639 | 5.60116 | 30 |
| | | SS | 6.9337 | 6.62111 | 30 |
| | | Total | 7.0156 | 5.78437 | 90 |
| Round 3 | DA | Conf | 6.8872 | 6.54260 | 15 |
| | | Sep | 10.4650 | 7.78143 | 15 |
| | | SS | 9.8600 | 6.15157 | 15 |
| | | Total | 9.0708 | 6.88673 | 45 |
| | No-DA | Conf | 5.6907 | 6.09325 | 15 |
| | | Sep | 4.4156 | 3.71905 | 15 |
| | | SS | 5.2174 | 5.26958 | 15 |
| | | Total | 5.1079 | 5.03318 | 45 |
| | Total | Conf | 6.2890 | 6.24169 | 30 |
| | | Sep | 7.4403 | 6.73593 | 30 |
| | | SS | 7.5387 | 6.10313 | 30 |
| | | Total | 7.0893 | 6.31992 | 90 |

Table C-17

*Reaction Time Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 9.3284 | 4.80274 | 15 |
| | Conf:No-DA | 6.3637 | 4.12231 | 15 |
| | Sep:DA | 12.1847 | 7.84598 | 15 |
| | Sep:No-DA | 9.1321 | 4.51744 | 15 |
| | SS:DA | 7.6408 | 8.49302 | 15 |
| | SS:No-DA | 7.1880 | 5.21545 | 15 |
| | Total | 8.6396 | 6.20127 | 90 |
| Round 2 | Conf:DA | 6.9306 | 4.71280 | 15 |
| | Conf:No-DA | 5.5680 | 5.55760 | 15 |
| | Sep:DA | 9.4293 | 6.70992 | 15 |
| | Sep:No-DA | 6.2985 | 3.83573 | 15 |
| | SS:DA | 7.6625 | 7.87949 | 15 |
| | SS:No-DA | 6.2048 | 5.25212 | 15 |
| | Total | 7.0156 | 5.78437 | 90 |
| Round 3 | Conf:DA | 6.8872 | 6.54260 | 15 |
| | Conf:No-DA | 5.6907 | 6.09325 | 15 |
| | Sep:DA | 10.4650 | 7.78143 | 15 |
| | Sep:No-DA | 4.4156 | 3.71905 | 15 |
| | SS:DA | 9.8600 | 6.15157 | 15 |
| | SS:No-DA | 5.2174 | 5.26958 | 15 |
| | Total | 7.0893 | 6.31992 | 90 |

Table C-18

*Mental Demand Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 6.93 | 4.559 | 15 |
| | | Sep | 9.40 | 5.289 | 15 |
| | | SS | 7.53 | 4.533 | 15 |
| | | Total | 7.96 | 4.815 | 45 |
| | No-DA | Conf | 10.93 | 4.496 | 15 |
| | | Sep | 10.53 | 4.422 | 15 |
| | | SS | 8.93 | 6.076 | 15 |
| | | Total | 10.13 | 5.016 | 45 |
| | Total | Conf | 8.93 | 4.891 | 30 |
| | | Sep | 9.97 | 4.824 | 30 |
| | | SS | 8.23 | 5.315 | 30 |
| | | Total | 9.04 | 5.010 | 90 |
| Round 2 | DA | Conf | 7.47 | 4.955 | 15 |
| | | Sep | 8.40 | 6.288 | 15 |
| | | SS | 5.67 | 4.483 | 15 |
| | | Total | 7.18 | 5.301 | 45 |
| | No-DA | Conf | 9.73 | 4.652 | 15 |
| | | Sep | 8.80 | 3.895 | 15 |
| | | SS | 6.93 | 6.638 | 15 |
| | | Total | 8.49 | 5.208 | 45 |
| | Total | Conf | 8.60 | 4.861 | 30 |
| | | Sep | 8.60 | 5.143 | 30 |
| | | SS | 6.30 | 5.603 | 30 |
| | | Total | 7.83 | 5.266 | 90 |
| Round 3 | DA | Conf | 9.93 | 4.891 | 15 |
| | | Sep | 11.60 | 5.986 | 15 |
| | | SS | 8.53 | 5.540 | 15 |
| | | Total | 10.02 | 5.512 | 45 |
| | No-DA | Conf | 11.27 | 5.800 | 15 |
| | | Sep | 10.13 | 5.194 | 15 |
| | | SS | 9.13 | 6.844 | 15 |
| | | Total | 10.18 | 5.913 | 45 |
| | Total | Conf | 10.60 | 5.315 | 30 |
| | | Sep | 10.87 | 5.557 | 30 |
| | | SS | 8.83 | 6.126 | 30 |
| | | Total | 10.10 | 5.685 | 90 |

Table C-19

*Mental Demand Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 6.93 | 4.559 | 15 |
| | Conf:No-DA | 10.93 | 4.496 | 15 |
| | Sep:DA | 9.40 | 5.289 | 15 |
| | Sep:No-DA | 10.53 | 4.422 | 15 |
| | SS:DA | 7.53 | 4.533 | 15 |
| | SS:No-DA | 8.93 | 6.076 | 15 |
| | Total | 9.04 | 5.010 | 90 |
| Round 2 | Conf:DA | 7.47 | 4.955 | 15 |
| | Conf:No-DA | 9.73 | 4.652 | 15 |
| | Sep:DA | 8.40 | 6.288 | 15 |
| | Sep:No-DA | 8.80 | 3.895 | 15 |
| | SS:DA | 5.67 | 4.483 | 15 |
| | SS:No-DA | 6.93 | 6.638 | 15 |
| | Total | 7.83 | 5.266 | 90 |
| Round 3 | Conf:DA | 9.93 | 4.891 | 15 |
| | Conf:No-DA | 11.27 | 5.800 | 15 |
| | Sep:DA | 11.60 | 5.986 | 15 |
| | Sep:No-DA | 10.13 | 5.194 | 15 |
| | SS:DA | 8.53 | 5.540 | 15 |
| | SS:No-DA | 9.13 | 6.844 | 15 |
| | Total | 10.10 | 5.685 | 90 |

Table C-20

*Physical Demand Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 2.00 | 3.586 | 15 |
| | | Sep | 4.27 | 5.625 | 15 |
| | | SS | 3.80 | 3.764 | 15 |
| | | Total | 3.36 | 4.432 | 45 |
| | No-DA | Conf | 2.47 | 2.997 | 15 |
| | | Sep | 2.87 | 4.373 | 15 |
| | | SS | 3.27 | 5.147 | 15 |
| | | Total | 2.87 | 4.181 | 45 |
| | Total | Conf | 2.23 | 3.256 | 30 |
| | | Sep | 3.57 | 5.001 | 30 |
| | | SS | 3.53 | 4.439 | 30 |
| | | Total | 3.11 | 4.291 | 90 |
| Round 2 | DA | Conf | 2.53 | 3.720 | 15 |
| | | Sep | 4.40 | 5.565 | 15 |
| | | SS | 4.33 | 4.152 | 15 |
| | | Total | 3.76 | 4.528 | 45 |
| | No-DA | Conf | 3.13 | 4.015 | 15 |
| | | Sep | 1.87 | 1.995 | 15 |
| | | SS | 3.20 | 4.814 | 15 |
| | | Total | 2.73 | 3.762 | 45 |
| | Total | Conf | 2.83 | 3.815 | 30 |
| | | Sep | 3.13 | 4.305 | 30 |
| | | SS | 3.77 | 4.454 | 30 |
| | | Total | 3.24 | 4.171 | 90 |
| Round 3 | DA | Conf | 2.47 | 3.182 | 15 |
| | | Sep | 6.27 | 7.304 | 15 |
| | | SS | 4.27 | 4.008 | 15 |
| | | Total | 4.33 | 5.270 | 45 |
| | No-DA | Conf | 4.27 | 5.824 | 15 |
| | | Sep | 4.13 | 2.997 | 15 |
| | | SS | 4.33 | 6.640 | 15 |
| | | Total | 4.24 | 5.262 | 45 |
| | Total | Conf | 3.37 | 4.701 | 30 |
| | | Sep | 5.20 | 5.592 | 30 |
| | | SS | 4.30 | 5.389 | 30 |
| | | Total | 4.29 | 5.237 | 90 |

Table C-21

*Physical Demand Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 2.00 | 3.586 | 15 |
| | Conf:No-DA | 2.47 | 2.997 | 15 |
| | Sep:DA | 4.27 | 5.625 | 15 |
| | Sep:No-DA | 2.87 | 4.373 | 15 |
| | SS:DA | 3.80 | 3.764 | 15 |
| | SS:No-DA | 3.27 | 5.147 | 15 |
| | Total | 3.11 | 4.291 | 90 |
| Round 2 | Conf:DA | 2.53 | 3.720 | 15 |
| | Conf:No-DA | 3.13 | 4.015 | 15 |
| | Sep:DA | 4.40 | 5.565 | 15 |
| | Sep:No-DA | 1.87 | 1.995 | 15 |
| | SS:DA | 4.33 | 4.152 | 15 |
| | SS:No-DA | 3.20 | 4.814 | 15 |
| | Total | 3.24 | 4.171 | 90 |
| Round 3 | Conf:DA | 2.47 | 3.182 | 15 |
| | Conf:No-DA | 4.27 | 5.824 | 15 |
| | Sep:DA | 6.27 | 7.304 | 15 |
| | Sep:No-DA | 4.13 | 2.997 | 15 |
| | SS:DA | 4.27 | 4.008 | 15 |
| | SS:No-DA | 4.33 | 6.640 | 15 |
| | Total | 4.29 | 5.237 | 90 |

Table C-22

*Temporal Demand Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 7.13 | 3.292 | 15 |
| | | Sep | 9.00 | 6.071 | 15 |
| | | SS | 7.33 | 4.716 | 15 |
| | | Total | 7.82 | 4.792 | 45 |
| | No-DA | Conf | 8.80 | 3.895 | 15 |
| | | Sep | 7.07 | 3.751 | 15 |
| | | SS | 7.93 | 5.444 | 15 |
| | | Total | 7.93 | 4.387 | 45 |
| | Total | Conf | 7.97 | 3.643 | 30 |
| | | Sep | 8.03 | 5.055 | 30 |
| | | SS | 7.63 | 5.014 | 30 |
| | | Total | 7.88 | 4.569 | 90 |
| Round 2 | DA | Conf | 6.67 | 3.677 | 15 |
| | | Sep | 8.00 | 5.305 | 15 |
| | | SS | 6.40 | 4.405 | 15 |
| | | Total | 7.02 | 4.464 | 45 |
| | No-DA | Conf | 7.13 | 3.777 | 15 |
| | | Sep | 6.47 | 3.159 | 15 |
| | | SS | 5.80 | 5.747 | 15 |
| | | Total | 6.47 | 4.304 | 45 |
| | Total | Conf | 6.90 | 3.670 | 30 |
| | | Sep | 7.23 | 4.360 | 30 |
| | | SS | 6.10 | 5.040 | 30 |
| | | Total | 6.74 | 4.369 | 90 |
| Round 3 | DA | Conf | 7.60 | 4.672 | 15 |
| | | Sep | 10.13 | 5.125 | 15 |
| | | SS | 8.27 | 4.148 | 15 |
| | | Total | 8.67 | 4.686 | 45 |
| | No-DA | Conf | 9.33 | 5.052 | 15 |
| | | Sep | 5.93 | 4.713 | 15 |
| | | SS | 7.80 | 6.494 | 15 |
| | | Total | 7.69 | 5.530 | 45 |
| | Total | Conf | 8.47 | 4.862 | 30 |
| | | Sep | 8.03 | 5.288 | 30 |
| | | SS | 8.03 | 5.359 | 30 |
| | | Total | 8.18 | 5.120 | 90 |

Table C-23

*Temporal Demand Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 7.13 | 3.292 | 15 |
| | Conf:No-DA | 8.80 | 3.895 | 15 |
| | Sep:DA | 9.00 | 6.071 | 15 |
| | Sep:No-DA | 7.07 | 3.751 | 15 |
| | SS:DA | 7.33 | 4.716 | 15 |
| | SS:No-DA | 7.93 | 5.444 | 15 |
| | Total | 7.88 | 4.569 | 90 |
| Round 2 | Conf:DA | 6.67 | 3.677 | 15 |
| | Conf:No-DA | 7.13 | 3.777 | 15 |
| | Sep:DA | 8.00 | 5.305 | 15 |
| | Sep:No-DA | 6.47 | 3.159 | 15 |
| | SS:DA | 6.40 | 4.405 | 15 |
| | SS:No-DA | 5.80 | 5.747 | 15 |
| | Total | 6.74 | 4.369 | 90 |
| Round 3 | Conf:DA | 7.60 | 4.672 | 15 |
| | Conf:No-DA | 9.33 | 5.052 | 15 |
| | Sep:DA | 10.13 | 5.125 | 15 |
| | Sep:No-DA | 5.93 | 4.713 | 15 |
| | SS:DA | 8.27 | 4.148 | 15 |
| | SS:No-DA | 7.80 | 6.494 | 15 |
| | Total | 8.18 | 5.120 | 90 |

Table C-24

*Performance Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 7.73 | 4.949 | 15 |
| | | Sep | 6.53 | 4.086 | 15 |
| | | SS | 4.27 | 3.674 | 15 |
| | | Total | 6.18 | 4.417 | 45 |
| | No-DA | Conf | 8.80 | 4.280 | 15 |
| | | Sep | 9.80 | 5.267 | 15 |
| | | SS | 9.87 | 6.093 | 15 |
| | | Total | 9.49 | 5.168 | 45 |
| | Total | Conf | 8.27 | 4.578 | 30 |
| | | Sep | 8.17 | 4.921 | 30 |
| | | SS | 7.07 | 5.705 | 30 |
| | | Total | 7.83 | 5.062 | 90 |
| Round 2 | DA | Conf | 6.60 | 5.742 | 15 |
| | | Sep | 7.93 | 4.906 | 15 |
| | | SS | 4.60 | 4.388 | 15 |
| | | Total | 6.38 | 5.118 | 45 |
| | No-DA | Conf | 7.27 | 5.216 | 15 |
| | | Sep | 8.73 | 5.106 | 15 |
| | | SS | 5.87 | 4.941 | 15 |
| | | Total | 7.29 | 5.111 | 45 |
| | Total | Conf | 6.93 | 5.401 | 30 |
| | | Sep | 8.33 | 4.936 | 30 |
| | | SS | 5.23 | 4.636 | 30 |
| | | Total | 6.83 | 5.106 | 90 |
| Round 3 | DA | Conf | 9.73 | 5.982 | 15 |
| | | Sep | 8.00 | 5.127 | 15 |
| | | SS | 9.00 | 3.946 | 15 |
| | | Total | 8.91 | 5.022 | 45 |
| | No-DA | Conf | 9.33 | 5.876 | 15 |
| | | Sep | 8.13 | 5.167 | 15 |
| | | SS | 7.60 | 5.082 | 15 |
| | | Total | 8.36 | 5.314 | 45 |
| | Total | Conf | 9.53 | 5.829 | 30 |
| | | Sep | 8.07 | 5.058 | 30 |
| | | SS | 8.30 | 4.527 | 30 |
| | | Total | 8.63 | 5.148 | 90 |

Table C-25

*Performance Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 7.73 | 4.949 | 15 |
| | Conf:No-DA | 8.80 | 4.280 | 15 |
| | Sep:DA | 6.53 | 4.086 | 15 |
| | Sep:No-DA | 9.80 | 5.267 | 15 |
| | SS:DA | 4.27 | 3.674 | 15 |
| | SS:No-DA | 9.87 | 6.093 | 15 |
| | Total | 7.83 | 5.062 | 90 |
| Round 2 | Conf:DA | 6.60 | 5.742 | 15 |
| | Conf:No-DA | 7.27 | 5.216 | 15 |
| | Sep:DA | 7.93 | 4.906 | 15 |
| | Sep:No-DA | 8.73 | 5.106 | 15 |
| | SS:DA | 4.60 | 4.388 | 15 |
| | SS:No-DA | 5.87 | 4.941 | 15 |
| | Total | 6.83 | 5.106 | 90 |
| Round 3 | Conf:DA | 9.73 | 5.982 | 15 |
| | Conf:No-DA | 9.33 | 5.876 | 15 |
| | Sep:DA | 8.00 | 5.127 | 15 |
| | Sep:No-DA | 8.13 | 5.167 | 15 |
| | SS:DA | 9.00 | 3.946 | 15 |
| | SS:No-DA | 7.60 | 5.082 | 15 |
| | Total | 8.63 | 5.148 | 90 |

Table C-26

*Effort Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 7.53 | 4.324 | 15 |
| | | Sep | 8.47 | 5.330 | 15 |
| | | SS | 8.60 | 6.069 | 15 |
| | | Total | 8.20 | 5.190 | 45 |
| | No-DA | Conf | 11.53 | 4.257 | 15 |
| | | Sep | 10.33 | 4.880 | 15 |
| | | SS | 8.07 | 6.100 | 15 |
| | | Total | 9.98 | 5.224 | 45 |
| | Total | Conf | 9.53 | 4.681 | 30 |
| | | Sep | 9.40 | 5.110 | 30 |
| | | SS | 8.33 | 5.985 | 30 |
| | | Total | 9.09 | 5.255 | 90 |
| Round 2 | DA | Conf | 6.73 | 4.217 | 15 |
| | | Sep | 7.27 | 5.077 | 15 |
| | | SS | 7.00 | 6.448 | 15 |
| | | Total | 7.00 | 5.209 | 45 |
| | No-DA | Conf | 9.80 | 4.523 | 15 |
| | | Sep | 9.93 | 4.713 | 15 |
| | | SS | 7.00 | 5.237 | 15 |
| | | Total | 8.91 | 4.917 | 45 |
| | Total | Conf | 8.27 | 4.571 | 30 |
| | | Sep | 8.60 | 5.001 | 30 |
| | | SS | 7.00 | 5.772 | 30 |
| | | Total | 7.96 | 5.127 | 90 |
| Round 3 | DA | Conf | 8.47 | 4.172 | 15 |
| | | Sep | 11.40 | 5.804 | 15 |
| | | SS | 10.67 | 5.864 | 15 |
| | | Total | 10.18 | 5.365 | 45 |
| | No-DA | Conf | 11.40 | 6.610 | 15 |
| | | Sep | 10.27 | 4.992 | 15 |
| | | SS | 8.67 | 6.388 | 15 |
| | | Total | 10.11 | 6.008 | 45 |
| | Total | Conf | 9.93 | 5.632 | 30 |
| | | Sep | 10.83 | 5.350 | 30 |
| | | SS | 9.67 | 6.110 | 30 |
| | | Total | 10.14 | 5.664 | 90 |

Table C-27

*Effort Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 7.53 | 4.324 | 15 |
| | Conf:No-DA | 11.53 | 4.257 | 15 |
| | Sep:DA | 8.47 | 5.330 | 15 |
| | Sep:No-DA | 10.33 | 4.880 | 15 |
| | SS:DA | 8.60 | 6.069 | 15 |
| | SS:No-DA | 8.07 | 6.100 | 15 |
| | Total | 9.09 | 5.255 | 90 |
| Round 2 | Conf:DA | 6.73 | 4.217 | 15 |
| | Conf:No-DA | 9.80 | 4.523 | 15 |
| | Sep:DA | 7.27 | 5.077 | 15 |
| | Sep:No-DA | 9.93 | 4.713 | 15 |
| | SS:DA | 7.00 | 6.448 | 15 |
| | SS:No-DA | 7.00 | 5.237 | 15 |
| | Total | 7.96 | 5.127 | 90 |
| Round 3 | Conf:DA | 8.47 | 4.172 | 15 |
| | Conf:No-DA | 11.40 | 6.610 | 15 |
| | Sep:DA | 11.40 | 5.804 | 15 |
| | Sep:No-DA | 10.27 | 4.992 | 15 |
| | SS:DA | 10.67 | 5.864 | 15 |
| | SS:No-DA | 8.67 | 6.388 | 15 |
| | Total | 10.14 | 5.664 | 90 |

Table C-28

*Frustration Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 3.73 | 4.234 | 15 |
| | | Sep | 6.80 | 5.321 | 15 |
| | | SS | 4.00 | 5.669 | 15 |
| | | Total | 4.84 | 5.187 | 45 |
| | No-DA | Conf | 8.73 | 5.650 | 15 |
| | | Sep | 7.53 | 5.854 | 15 |
| | | SS | 5.20 | 5.321 | 15 |
| | | Total | 7.16 | 5.681 | 45 |
| | Total | Conf | 6.23 | 5.525 | 30 |
| | | Sep | 7.17 | 5.509 | 30 |
| | | SS | 4.60 | 5.437 | 30 |
| | | Total | 6.00 | 5.532 | 90 |
| Round 2 | DA | Conf | 3.87 | 5.263 | 15 |
| | | Sep | 7.07 | 6.147 | 15 |
| | | SS | 3.13 | 3.204 | 15 |
| | | Total | 4.69 | 5.204 | 45 |
| | No-DA | Conf | 6.07 | 5.284 | 15 |
| | | Sep | 7.40 | 6.010 | 15 |
| | | SS | 2.87 | 3.583 | 15 |
| | | Total | 5.44 | 5.307 | 45 |
| | Total | Conf | 4.97 | 5.301 | 30 |
| | | Sep | 7.23 | 5.975 | 30 |
| | | SS | 3.00 | 3.343 | 30 |
| | | Total | 5.07 | 5.240 | 90 |
| Round 3 | DA | Conf | 6.20 | 6.144 | 15 |
| | | Sep | 8.47 | 6.578 | 15 |
| | | SS | 7.13 | 5.097 | 15 |
| | | Total | 7.27 | 5.910 | 45 |
| | No-DA | Conf | 6.47 | 4.926 | 15 |
| | | Sep | 7.73 | 5.800 | 15 |
| | | SS | 4.47 | 5.357 | 15 |
| | | Total | 6.22 | 5.423 | 45 |
| | Total | Conf | 6.33 | 5.473 | 30 |
| | | Sep | 8.10 | 6.105 | 30 |
| | | SS | 5.80 | 5.314 | 30 |
| | | Total | 6.74 | 5.664 | 90 |

Table C-29

*Frustration Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 3.73 | 4.234 | 15 |
| | Conf:No-DA | 8.73 | 5.650 | 15 |
| | Sep:DA | 6.80 | 5.321 | 15 |
| | Sep:No-DA | 7.53 | 5.854 | 15 |
| | SS:DA | 4.00 | 5.669 | 15 |
| | SS:No-DA | 5.20 | 5.321 | 15 |
| | Total | 6.00 | 5.532 | 90 |
| Round 2 | Conf:DA | 3.87 | 5.263 | 15 |
| | Conf:No-DA | 6.07 | 5.284 | 15 |
| | Sep:DA | 7.07 | 6.147 | 15 |
| | Sep:No-DA | 7.40 | 6.010 | 15 |
| | SS:DA | 3.13 | 3.204 | 15 |
| | SS:No-DA | 2.87 | 3.583 | 15 |
| | Total | 5.07 | 5.240 | 90 |
| Round 3 | Conf:DA | 6.20 | 6.144 | 15 |
| | Conf:No-DA | 6.47 | 4.926 | 15 |
| | Sep:DA | 8.47 | 6.578 | 15 |
| | Sep:No-DA | 7.73 | 5.800 | 15 |
| | SS:DA | 7.13 | 5.097 | 15 |
| | SS:No-DA | 4.47 | 5.357 | 15 |
| | Total | 6.74 | 5.664 | 90 |

Table C-30

*Composite Score Descriptive Statistics by Automation Type, Display Type and Simulation Round*

| Simulation Round | Automation Type | Display Type | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| Round 1 | DA | Conf | 35.07 | 15.581 | 15 |
| | | Sep | 44.47 | 23.655 | 15 |
| | | SS | 35.53 | 22.129 | 15 |
| | | Total | 38.36 | 20.742 | 45 |
| | No-DA | Conf | 51.27 | 15.182 | 15 |
| | | Sep | 48.13 | 18.256 | 15 |
| | | SS | 43.27 | 22.483 | 15 |
| | | Total | 47.56 | 18.743 | 45 |
| | Total | Conf | 43.17 | 17.215 | 30 |
| | | Sep | 46.30 | 20.844 | 30 |
| | | SS | 39.40 | 22.269 | 30 |
| | | Total | 42.96 | 20.193 | 90 |
| Round 2 | DA | Conf | 33.87 | 18.232 | 15 |
| | | Sep | 43.07 | 26.980 | 15 |
| | | SS | 31.13 | 20.622 | 15 |
| | | Total | 36.02 | 22.346 | 45 |
| | No-DA | Conf | 43.13 | 19.172 | 15 |
| | | Sep | 43.20 | 18.606 | 15 |
| | | SS | 31.67 | 20.212 | 15 |
| | | Total | 39.33 | 19.676 | 45 |
| | Total | Conf | 38.50 | 18.977 | 30 |
| | | Sep | 43.13 | 22.771 | 30 |
| | | SS | 31.40 | 20.065 | 30 |
| | | Total | 37.68 | 21.001 | 90 |
| Round 3 | DA | Conf | 44.40 | 18.372 | 15 |
| | | Sep | 55.87 | 30.984 | 15 |
| | | SS | 47.87 | 22.408 | 15 |
| | | Total | 49.38 | 24.417 | 45 |
| | No-DA | Conf | 52.07 | 23.212 | 15 |
| | | Sep | 46.33 | 23.240 | 15 |
| | | SS | 42.00 | 27.216 | 15 |
| | | Total | 46.80 | 24.420 | 45 |
| | Total | Conf | 48.23 | 20.935 | 30 |
| | | Sep | 51.10 | 27.344 | 30 |
| | | SS | 44.93 | 24.676 | 30 |
| | | Total | 48.09 | 24.316 | 90 |

Table C-31

*Composite Score Descriptive Statistics by DT:AT Condition and Simulation Round*

| Simulation Round | Condition | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Round 1 | Conf:DA | 35.07 | 15.581 | 15 |
| | Conf:No-DA | 51.27 | 15.182 | 15 |
| | Sep:DA | 44.47 | 23.655 | 15 |
| | Sep:No-DA | 48.13 | 18.256 | 15 |
| | SS:DA | 35.53 | 22.129 | 15 |
| | SS:No-DA | 43.27 | 22.483 | 15 |
| | Total | 42.96 | 20.193 | 90 |
| Round 2 | Conf:DA | 33.87 | 18.232 | 15 |
| | Conf:No-DA | 43.13 | 19.172 | 15 |
| | Sep:DA | 43.07 | 26.980 | 15 |
| | Sep:No-DA | 43.20 | 18.606 | 15 |
| | SS:DA | 31.13 | 20.622 | 15 |
| | SS:No-DA | 31.67 | 20.212 | 15 |
| | Total | 37.68 | 21.001 | 90 |
| Round 3 | Conf:DA | 44.40 | 18.372 | 15 |
| | Conf:No-DA | 52.07 | 23.212 | 15 |
| | Sep:DA | 55.87 | 30.984 | 15 |
| | Sep:No-DA | 46.33 | 23.240 | 15 |
| | SS:DA | 47.87 | 22.408 | 15 |
| | SS:No-DA | 42.00 | 27.216 | 15 |
| | Total | 48.09 | 24.316 | 90 |

## Appendix D

Table D-1

*Net Income RTM Delta Multiple Regression Descriptive Statistics for Total Participant Population*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Net Income RTM Delta | -396286.00 | 1812790.65 | 90 |
| Assessment Score | 0.51 | 6.077 | 90 |
| Damage Omission Errors - Round 1 | 78.29 | 119.426 | 90 |
| Demand Omission Errors - Round 1 | 213.73 | 183.281 | 90 |
| Demand Commission Error Rate - Round 1 | 0.1755 | 0.07896 | 90 |
| Damage Commission Error Rate - Round 1 | 0.1259 | 0.10936 | 90 |
| Damage Omission Errors - Round 2 | 73.99 | 175.473 | 90 |
| Demand Omission Errors - Round 2 | 136.01 | 150.642 | 90 |
| Demand Commission Error Rate - Round 2 | 0.1484 | 0.07311 | 90 |
| Damage Commission Error Rate - Round 2 | 0.0850 | 0.09566 | 90 |
| Mental Demand - Round 1 | 9.04 | 5.010 | 90 |
| Physical Demand - Round 1 | 3.11 | 4.291 | 90 |
| Temporal Demand - Round 1 | 7.88 | 4.569 | 90 |
| Performance - Round 1 | 7.83 | 5.062 | 90 |
| Effort - Round 1 | 9.09 | 5.255 | 90 |
| Frustration - Round 1 | 6.00 | 5.532 | 90 |
| Composite Score - Round 1 | 42.96 | 20.193 | 90 |
| Mental Demand - Round 2 | 7.83 | 5.266 | 90 |
| Physical Demand - Round 2 | 3.24 | 4.171 | 90 |
| Temporal Demand - Round 2 | 6.74 | 4.369 | 90 |
| Performance - Round 2 | 6.83 | 5.106 | 90 |
| Effort - Round 2 | 7.96 | 5.127 | 90 |
| Frustration - Round 2 | 5.07 | 5.240 | 90 |
| Composite Score - Round 2 | 37.68 | 21.001 | 90 |
| Reaction Time - Round 1 | 8.6396 | 6.20127 | 90 |
| Reaction Time - Round 2 | 7.0156 | 5.78437 | 90 |

Table D-2

*Net Income RTM Delta Multiple Regression Descriptive Statistics for Automation Type - Decision Automation*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Net Income RTM Delta | -1185350.67 | 1628961.57 | 45 |
| Assessment Score | -0.27 | 6.972 | 45 |
| Damage Omission Errors - Round 1 | 42.49 | 87.482 | 45 |
| Demand Omission Errors - Round 1 | 128.89 | 140.971 | 45 |
| Demand Commission Error Rate - Round 1 | 0.1297 | 0.06033 | 45 |
| Damage Commission Error Rate - Round 1 | 0.1080 | 0.11230 | 45 |
| Damage Omission Errors - Round 2 | 44.31 | 132.152 | 45 |
| Demand Omission Errors - Round 2 | 73.38 | 93.201 | 45 |
| Demand Commission Error Rate - Round 2 | 0.1305 | 0.06857 | 45 |
| Damage Commission Error Rate - Round 2 | 0.0841 | 0.10808 | 45 |
| Mental Demand - Round 1 | 7.96 | 4.815 | 45 |
| Physical Demand - Round 1 | 3.36 | 4.432 | 45 |
| Temporal Demand - Round 1 | 7.82 | 4.792 | 45 |
| Performance - Round 1 | 6.18 | 4.417 | 45 |
| Effort - Round 1 | 8.20 | 5.190 | 45 |
| Frustration - Round 1 | 4.84 | 5.187 | 45 |
| Composite Score - Round 1 | 38.36 | 20.742 | 45 |
| Mental Demand - Round 2 | 7.18 | 5.301 | 45 |
| Physical Demand - Round 2 | 3.76 | 4.528 | 45 |
| Temporal Demand - Round 2 | 7.02 | 4.464 | 45 |
| Performance - Round 2 | 6.38 | 5.118 | 45 |
| Effort - Round 2 | 7.00 | 5.209 | 45 |
| Frustration - Round 2 | 4.69 | 5.204 | 45 |
| Composite Score - Round 2 | 36.02 | 22.346 | 45 |
| Reaction Time - Round 1 | 9.7179 | 7.31261 | 45 |
| Reaction Time - Round 2 | 8.0075 | 6.50171 | 45 |

Table D-3

*Net Income RTM Delta Multiple Regression Descriptive Statistics for Automation Type – No Decision Automation*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Net Income RTM Delta | 392778.67 | 1649255.44 | 45 |
| Assessment Score | 1.29 | 4.985 | 45 |
| Damage Omission Errors - Round 1 | 114.09 | 136.289 | 45 |
| Demand Omission Errors - Round 1 | 298.58 | 182.621 | 45 |
| Demand Commission Error Rate - Round 1 | 0.2213 | 0.06845 | 45 |
| Damage Commission Error Rate - Round 1 | 0.1438 | 0.10453 | 45 |
| Damage Omission Errors - Round 2 | 103.67 | 207.402 | 45 |
| Demand Omission Errors - Round 2 | 198.64 | 170.854 | 45 |
| Demand Commission Error Rate - Round 2 | 0.1664 | 0.07384 | 45 |
| Damage Commission Error Rate - Round 2 | 0.0859 | 0.08263 | 45 |
| Mental Demand - Round 1 | 10.13 | 5.016 | 45 |
| Physical Demand - Round 1 | 2.87 | 4.181 | 45 |
| Temporal Demand - Round 1 | 7.93 | 4.387 | 45 |
| Performance - Round 1 | 9.49 | 5.168 | 45 |
| Effort - Round 1 | 9.98 | 5.224 | 45 |
| Frustration - Round 1 | 7.16 | 5.681 | 45 |
| Composite Score - Round 1 | 47.56 | 18.743 | 45 |
| Mental Demand - Round 2 | 8.49 | 5.208 | 45 |
| Physical Demand - Round 2 | 2.73 | 3.762 | 45 |
| Temporal Demand - Round 2 | 6.47 | 4.304 | 45 |
| Performance - Round 2 | 7.29 | 5.111 | 45 |
| Effort - Round 2 | 8.91 | 4.917 | 45 |
| Frustration - Round 2 | 5.44 | 5.307 | 45 |
| Composite Score - Round 2 | 39.33 | 19.676 | 45 |
| Reaction Time - Round 1 | 7.5613 | 4.68324 | 45 |
| Reaction Time - Round 2 | 6.0238 | 4.83670 | 45 |

Table D-4

*Net Income RTM Delta Multiple Regression Descriptive Statistics for Display Type – Configural*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Net Income RTM Delta | -146487.00 | 2004244.38 | 30 |
| Assessment Score | 2.00 | 5.363 | 30 |
| Damage Omission Errors - Round 1 | 72.10 | 103.846 | 30 |
| Demand Omission Errors - Round 1 | 218.67 | 173.148 | 30 |
| Demand Commission Error Rate - Round 1 | 0.1721 | 0.07473 | 30 |
| Damage Commission Error Rate - Round 1 | 0.1252 | 0.09753 | 30 |
| Damage Omission Errors - Round 2 | 53.47 | 116.381 | 30 |
| Demand Omission Errors - Round 2 | 147.90 | 160.520 | 30 |
| Demand Commission Error Rate - Round 2 | 0.1682 | 0.07757 | 30 |
| Damage Commission Error Rate - Round 2 | 0.0822 | 0.08394 | 30 |
| Mental Demand - Round 1 | 8.93 | 4.891 | 30 |
| Physical Demand - Round 1 | 2.23 | 3.256 | 30 |
| Temporal Demand - Round 1 | 7.97 | 3.643 | 30 |
| Performance - Round 1 | 8.27 | 4.578 | 30 |
| Effort - Round 1 | 9.53 | 4.681 | 30 |
| Frustration - Round 1 | 6.23 | 5.525 | 30 |
| Composite Score - Round 1 | 43.17 | 17.215 | 30 |
| Mental Demand - Round 2 | 8.60 | 4.861 | 30 |
| Physical Demand - Round 2 | 2.83 | 3.815 | 30 |
| Temporal Demand - Round 2 | 6.90 | 3.670 | 30 |
| Performance - Round 2 | 6.93 | 5.401 | 30 |
| Effort - Round 2 | 8.27 | 4.571 | 30 |
| Frustration - Round 2 | 4.97 | 5.301 | 30 |
| Composite Score - Round 2 | 38.50 | 18.977 | 30 |
| Reaction Time - Round 1 | 7.8460 | 4.64891 | 30 |
| Reaction Time - Round 2 | 6.2493 | 5.11013 | 30 |

Table D-5

*Net Income RTM Delta Multiple Regression Descriptive Statistics for Display Type – Separable*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Net Income RTM Delta | -199119.00 | 1976698.90 | 30 |
| Assessment Score | 0.53 | 6.564 | 30 |
| Damage Omission Errors - Round 1 | 59.63 | 100.037 | 30 |
| Demand Omission Errors - Round 1 | 249.10 | 210.189 | 30 |
| Demand Commission Error Rate - Round 1 | 0.1959 | 0.08906 | 30 |
| Damage Commission Error Rate - Round 1 | 0.1258 | 0.10925 | 30 |
| Damage Omission Errors - Round 2 | 58.27 | 112.377 | 30 |
| Demand Omission Errors - Round 2 | 174.57 | 168.615 | 30 |
| Demand Commission Error Rate - Round 2 | 0.1524 | 0.07742 | 30 |
| Damage Commission Error Rate - Round 2 | 0.0949 | 0.08885 | 30 |
| Mental Demand - Round 1 | 9.97 | 4.824 | 30 |
| Physical Demand - Round 1 | 3.57 | 5.001 | 30 |
| Temporal Demand - Round 1 | 8.03 | 5.055 | 30 |
| Performance - Round 1 | 8.17 | 4.921 | 30 |
| Effort - Round 1 | 9.40 | 5.110 | 30 |
| Frustration - Round 1 | 7.17 | 5.509 | 30 |
| Composite Score - Round 1 | 46.30 | 20.844 | 30 |
| Mental Demand - Round 2 | 8.60 | 5.143 | 30 |
| Physical Demand - Round 2 | 3.13 | 4.305 | 30 |
| Temporal Demand - Round 2 | 7.23 | 4.360 | 30 |
| Performance - Round 2 | 8.33 | 4.936 | 30 |
| Effort - Round 2 | 8.60 | 5.001 | 30 |
| Frustration - Round 2 | 7.23 | 5.975 | 30 |
| Composite Score - Round 2 | 43.13 | 22.771 | 30 |
| Reaction Time - Round 1 | 10.6584 | 6.47919 | 30 |
| Reaction Time - Round 2 | 7.8639 | 5.60116 | 30 |

Table D-6

*Net Income RTM Delta Multiple Regression Descriptive Statistics for Display Type – Semantic-Spatial*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Net Income RTM Delta | -843252.00 | 1359962.05 | 30 |
| Assessment Score | -1.00 | 6.069 | 30 |
| Damage Omission Errors - Round 1 | 103.13 | 148.128 | 30 |
| Demand Omission Errors - Round 1 | 173.43 | 161.039 | 30 |
| Demand Commission Error Rate - Round 1 | 0.1585 | 0.06986 | 30 |
| Damage Commission Error Rate - Round 1 | 0.1266 | 0.12351 | 30 |
| Damage Omission Errors - Round 2 | 110.23 | 257.434 | 30 |
| Demand Omission Errors - Round 2 | 85.57 | 105.498 | 30 |
| Demand Commission Error Rate - Round 2 | 0.1247 | 0.05819 | 30 |
| Damage Commission Error Rate - Round 2 | 0.0779 | 0.11394 | 30 |
| Mental Demand - Round 1 | 8.23 | 5.315 | 30 |
| Physical Demand - Round 1 | 3.53 | 4.439 | 30 |
| Temporal Demand - Round 1 | 7.63 | 5.014 | 30 |
| Performance - Round 1 | 7.07 | 5.705 | 30 |
| Effort - Round 1 | 8.33 | 5.985 | 30 |
| Frustration - Round 1 | 4.60 | 5.437 | 30 |
| Composite Score - Round 1 | 39.40 | 22.269 | 30 |
| Mental Demand - Round 2 | 6.30 | 5.603 | 30 |
| Physical Demand - Round 2 | 3.77 | 4.454 | 30 |
| Temporal Demand - Round 2 | 6.10 | 5.040 | 30 |
| Performance - Round 2 | 5.23 | 4.636 | 30 |
| Effort - Round 2 | 7.00 | 5.772 | 30 |
| Frustration - Round 2 | 3.00 | 3.343 | 30 |
| Composite Score - Round 2 | 31.40 | 20.065 | 30 |
| Reaction Time - Round 1 | 7.4144 | 6.92868 | 30 |
| Reaction Time - Round 2 | 6.9337 | 6.62111 | 30 |

Table D-7

*Production Delta RTM Delta Multiple Regression Descriptive Statistics for Total Participant Population*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Production Delta RTM Delta | 1.06 | 17.02 | 90 |
| Assessment Score | 0.51 | 6.077 | 90 |
| Damage Omission Errors - Round 1 | 78.29 | 119.426 | 90 |
| Demand Omission Errors - Round 1 | 213.73 | 183.281 | 90 |
| Demand Commission Error Rate - Round 1 | 0.1755 | 0.07896 | 90 |
| Damage Commission Error Rate - Round 1 | 0.1259 | 0.10936 | 90 |
| Damage Omission Errors - Round 2 | 73.99 | 175.473 | 90 |
| Demand Omission Errors - Round 2 | 136.01 | 150.642 | 90 |
| Demand Commission Error Rate - Round 2 | 0.1484 | 0.07311 | 90 |
| Damage Commission Error Rate - Round 2 | 0.0850 | 0.09566 | 90 |
| Mental Demand - Round 1 | 9.04 | 5.010 | 90 |
| Physical Demand - Round 1 | 3.11 | 4.291 | 90 |
| Temporal Demand - Round 1 | 7.88 | 4.569 | 90 |
| Performance - Round 1 | 7.83 | 5.062 | 90 |
| Effort - Round 1 | 9.09 | 5.255 | 90 |
| Frustration - Round 1 | 6.00 | 5.532 | 90 |
| Composite Score - Round 1 | 42.96 | 20.193 | 90 |
| Mental Demand - Round 2 | 7.83 | 5.266 | 90 |
| Physical Demand - Round 2 | 3.24 | 4.171 | 90 |
| Temporal Demand - Round 2 | 6.74 | 4.369 | 90 |
| Performance - Round 2 | 6.83 | 5.106 | 90 |
| Effort - Round 2 | 7.96 | 5.127 | 90 |
| Frustration - Round 2 | 5.07 | 5.240 | 90 |
| Composite Score - Round 2 | 37.68 | 21.001 | 90 |
| Reaction Time - Round 1 | 8.6396 | 6.20127 | 90 |
| Reaction Time - Round 2 | 7.0156 | 5.78437 | 90 |

Table D-8

*Production Delta RTM Delta Multiple Regression Descriptive Statistics for Automation Type – Decision Automation*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Production Delta RTM Delta | 7.58 | 14.25 | 45 |
| Assessment Score | -0.27 | 6.972 | 45 |
| Damage Omission Errors - Round 1 | 42.49 | 87.482 | 45 |
| Demand Omission Errors - Round 1 | 128.89 | 140.971 | 45 |
| Demand Commission Error Rate - Round 1 | 0.1297 | 0.06033 | 45 |
| Damage Commission Error Rate - Round 1 | 0.1080 | 0.11230 | 45 |
| Damage Omission Errors - Round 2 | 44.31 | 132.152 | 45 |
| Demand Omission Errors - Round 2 | 73.38 | 93.201 | 45 |
| Demand Commission Error Rate - Round 2 | 0.1305 | 0.06857 | 45 |
| Damage Commission Error Rate - Round 2 | 0.0841 | 0.10808 | 45 |
| Mental Demand - Round 1 | 7.96 | 4.815 | 45 |
| Physical Demand - Round 1 | 3.36 | 4.432 | 45 |
| Temporal Demand - Round 1 | 7.82 | 4.792 | 45 |
| Performance - Round 1 | 6.18 | 4.417 | 45 |
| Effort - Round 1 | 8.20 | 5.190 | 45 |
| Frustration - Round 1 | 4.84 | 5.187 | 45 |
| Composite Score - Round 1 | 38.36 | 20.742 | 45 |
| Mental Demand - Round 2 | 7.18 | 5.301 | 45 |
| Physical Demand - Round 2 | 3.76 | 4.528 | 45 |
| Temporal Demand - Round 2 | 7.02 | 4.464 | 45 |
| Performance - Round 2 | 6.38 | 5.118 | 45 |
| Effort - Round 2 | 7.00 | 5.209 | 45 |
| Frustration - Round 2 | 4.69 | 5.204 | 45 |
| Composite Score - Round 2 | 36.02 | 22.346 | 45 |
| Reaction Time - Round 1 | 9.7179 | 7.31261 | 45 |
| Reaction Time - Round 2 | 8.0075 | 6.50171 | 45 |

Table D-9

*Production Delta RTM Delta Multiple Regression Descriptive Statistics for Automation Type – No Decision Automation*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Production Delta RTM Delta | -5.47 | 17.20 | 45 |
| Assessment Score | 1.29 | 4.985 | 45 |
| Damage Omission Errors - Round 1 | 114.09 | 136.289 | 45 |
| Demand Omission Errors - Round 1 | 298.58 | 182.621 | 45 |
| Demand Commission Error Rate - Round 1 | 0.2213 | 0.06845 | 45 |
| Damage Commission Error Rate - Round 1 | 0.1438 | 0.10453 | 45 |
| Damage Omission Errors - Round 2 | 103.67 | 207.402 | 45 |
| Demand Omission Errors - Round 2 | 198.64 | 170.854 | 45 |
| Demand Commission Error Rate - Round 2 | 0.1664 | 0.07384 | 45 |
| Damage Commission Error Rate - Round 2 | 0.0859 | 0.08263 | 45 |
| Mental Demand - Round 1 | 10.13 | 5.016 | 45 |
| Physical Demand - Round 1 | 2.87 | 4.181 | 45 |
| Temporal Demand - Round 1 | 7.93 | 4.387 | 45 |
| Performance - Round 1 | 9.49 | 5.168 | 45 |
| Effort - Round 1 | 9.98 | 5.224 | 45 |
| Frustration - Round 1 | 7.16 | 5.681 | 45 |
| Composite Score - Round 1 | 47.56 | 18.743 | 45 |
| Mental Demand - Round 2 | 8.49 | 5.208 | 45 |
| Physical Demand - Round 2 | 2.73 | 3.762 | 45 |
| Temporal Demand - Round 2 | 6.47 | 4.304 | 45 |
| Performance - Round 2 | 7.29 | 5.111 | 45 |
| Effort - Round 2 | 8.91 | 4.917 | 45 |
| Frustration - Round 2 | 5.44 | 5.307 | 45 |
| Composite Score - Round 2 | 39.33 | 19.676 | 45 |
| Reaction Time - Round 1 | 7.5613 | 4.68324 | 45 |
| Reaction Time - Round 2 | 6.0238 | 4.83670 | 45 |

Table D-10

*Production Delta RTM Delta Multiple Regression Descriptive Statistics for Display Type - Configural*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Production Delta RTM Delta | -0.3667 | 19.35954 | 30 |
| Assessment Score | 2.00 | 5.363 | 30 |
| Damage Omission Errors - Round 1 | 72.10 | 103.846 | 30 |
| Demand Omission Errors - Round 1 | 218.67 | 173.148 | 30 |
| Demand Commission Error Rate - Round 1 | 0.1721 | 0.07473 | 30 |
| Damage Commission Error Rate - Round 1 | 0.1252 | 0.09753 | 30 |
| Damage Omission Errors - Round 2 | 53.47 | 116.381 | 30 |
| Demand Omission Errors - Round 2 | 147.90 | 160.520 | 30 |
| Demand Commission Error Rate - Round 2 | 0.1682 | 0.07757 | 30 |
| Damage Commission Error Rate - Round 2 | 0.0822 | 0.08394 | 30 |
| Mental Demand - Round 1 | 8.93 | 4.891 | 30 |
| Physical Demand - Round 1 | 2.23 | 3.256 | 30 |
| Temporal Demand - Round 1 | 7.97 | 3.643 | 30 |
| Performance - Round 1 | 8.27 | 4.578 | 30 |
| Effort - Round 1 | 9.53 | 4.681 | 30 |
| Frustration - Round 1 | 6.23 | 5.525 | 30 |
| Composite Score - Round 1 | 43.17 | 17.215 | 30 |
| Mental Demand - Round 2 | 8.60 | 4.861 | 30 |
| Physical Demand - Round 2 | 2.83 | 3.815 | 30 |
| Temporal Demand - Round 2 | 6.90 | 3.670 | 30 |
| Performance - Round 2 | 6.93 | 5.401 | 30 |
| Effort - Round 2 | 8.27 | 4.571 | 30 |
| Frustration - Round 2 | 4.97 | 5.301 | 30 |
| Composite Score - Round 2 | 38.50 | 18.977 | 30 |
| Reaction Time - Round 1 | 7.8460 | 4.64891 | 30 |
| Reaction Time - Round 2 | 6.2493 | 5.11013 | 30 |

Table D-11

*Production Delta RTM Delta Multiple Regression Descriptive Statistics for Display Type - Separable*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Production Delta RTM Delta | -1.3333 | 19.93668 | 30 |
| Assessment Score | 0.53 | 6.564 | 30 |
| Damage Omission Errors - Round 1 | 59.63 | 100.037 | 30 |
| Demand Omission Errors - Round 1 | 249.10 | 210.189 | 30 |
| Demand Commission Error Rate - Round 1 | 0.1959 | 0.08906 | 30 |
| Damage Commission Error Rate - Round 1 | 0.1258 | 0.10925 | 30 |
| Damage Omission Errors - Round 2 | 58.27 | 112.377 | 30 |
| Demand Omission Errors - Round 2 | 174.57 | 168.615 | 30 |
| Demand Commission Error Rate - Round 2 | 0.1524 | 0.07742 | 30 |
| Damage Commission Error Rate - Round 2 | 0.0949 | 0.08885 | 30 |
| Mental Demand - Round 1 | 9.97 | 4.824 | 30 |
| Physical Demand - Round 1 | 3.57 | 5.001 | 30 |
| Temporal Demand - Round 1 | 8.03 | 5.055 | 30 |
| Performance - Round 1 | 8.17 | 4.921 | 30 |
| Effort - Round 1 | 9.40 | 5.110 | 30 |
| Frustration - Round 1 | 7.17 | 5.509 | 30 |
| Composite Score - Round 1 | 46.30 | 20.844 | 30 |
| Mental Demand - Round 2 | 8.60 | 5.143 | 30 |
| Physical Demand - Round 2 | 3.13 | 4.305 | 30 |
| Temporal Demand - Round 2 | 7.23 | 4.360 | 30 |
| Performance - Round 2 | 8.33 | 4.936 | 30 |
| Effort - Round 2 | 8.60 | 5.001 | 30 |
| Frustration - Round 2 | 7.23 | 5.975 | 30 |
| Composite Score - Round 2 | 43.13 | 22.771 | 30 |
| Reaction Time - Round 1 | 10.6584 | 6.47919 | 30 |
| Reaction Time - Round 2 | 7.8639 | 5.60116 | 30 |

Table D-12

*Production Delta RTM Delta Multiple Regression Descriptive Statistics for Display Type – Semantic-Spatial*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Production Delta RTM Delta | 4.8667 | 9.67661 | 30 |
| Assessment Score | -1.00 | 6.069 | 30 |
| Damage Omission Errors - Round 1 | 103.13 | 148.128 | 30 |
| Demand Omission Errors - Round 1 | 173.43 | 161.039 | 30 |
| Demand Commission Error Rate - Round 1 | 0.1585 | 0.06986 | 30 |
| Damage Commission Error Rate - Round 1 | 0.1266 | 0.12351 | 30 |
| Damage Omission Errors - Round 2 | 110.23 | 257.434 | 30 |
| Demand Omission Errors - Round 2 | 85.57 | 105.498 | 30 |
| Demand Commission Error Rate - Round 2 | 0.1247 | 0.05819 | 30 |
| Damage Commission Error Rate - Round 2 | 0.0779 | 0.11394 | 30 |
| Mental Demand - Round 1 | 8.23 | 5.315 | 30 |
| Physical Demand - Round 1 | 3.53 | 4.439 | 30 |
| Temporal Demand - Round 1 | 7.63 | 5.014 | 30 |
| Performance - Round 1 | 7.07 | 5.705 | 30 |
| Effort - Round 1 | 8.33 | 5.985 | 30 |
| Frustration - Round 1 | 4.60 | 5.437 | 30 |
| Composite Score - Round 1 | 39.40 | 22.269 | 30 |
| Mental Demand - Round 2 | 6.30 | 5.603 | 30 |
| Physical Demand - Round 2 | 3.77 | 4.454 | 30 |
| Temporal Demand - Round 2 | 6.10 | 5.040 | 30 |
| Performance - Round 2 | 5.23 | 4.636 | 30 |
| Effort - Round 2 | 7.00 | 5.772 | 30 |
| Frustration - Round 2 | 3.00 | 3.343 | 30 |
| Composite Score - Round 2 | 31.40 | 20.065 | 30 |
| Reaction Time - Round 1 | 7.4144 | 6.92868 | 30 |
| Reaction Time - Round 2 | 6.9337 | 6.62111 | 30 |

Table D-13

*Repair Cost RTM Delta Multiple Regression Descriptive Statistics for Total Participant Population*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Repair Cost RTM Delta | 288825.00 | 654460.98 | 90 |
| Assessment Score | 0.51 | 6.077 | 90 |
| Damage Omission Errors - Round 1 | 78.29 | 119.426 | 90 |
| Demand Omission Errors - Round 1 | 213.73 | 183.281 | 90 |
| Demand Commission Error Rate - Round 1 | 0.1755 | 0.07896 | 90 |
| Damage Commission Error Rate - Round 1 | 0.1259 | 0.10936 | 90 |
| Damage Omission Errors - Round 2 | 73.99 | 175.473 | 90 |
| Demand Omission Errors - Round 2 | 136.01 | 150.642 | 90 |
| Demand Commission Error Rate - Round 2 | 0.1484 | 0.07311 | 90 |
| Damage Commission Error Rate - Round 2 | 0.0850 | 0.09566 | 90 |
| Mental Demand - Round 1 | 9.04 | 5.010 | 90 |
| Physical Demand - Round 1 | 3.11 | 4.291 | 90 |
| Temporal Demand - Round 1 | 7.88 | 4.569 | 90 |
| Performance - Round 1 | 7.83 | 5.062 | 90 |
| Effort - Round 1 | 9.09 | 5.255 | 90 |
| Frustration - Round 1 | 6.00 | 5.532 | 90 |
| Composite Score - Round 1 | 42.96 | 20.193 | 90 |
| Mental Demand - Round 2 | 7.83 | 5.266 | 90 |
| Physical Demand - Round 2 | 3.24 | 4.171 | 90 |
| Temporal Demand - Round 2 | 6.74 | 4.369 | 90 |
| Performance - Round 2 | 6.83 | 5.106 | 90 |
| Effort - Round 2 | 7.96 | 5.127 | 90 |
| Frustration - Round 2 | 5.07 | 5.240 | 90 |
| Composite Score - Round 2 | 37.68 | 21.001 | 90 |
| Reaction Time - Round 1 | 8.6396 | 6.20127 | 90 |
| Reaction Time - Round 2 | 7.0156 | 5.78437 | 90 |

Table D-14

*Repair Cost RTM Delta Multiple Regression Descriptive Statistics for Automation Type – Decision Automation*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Repair Cost RTM Delta | 435316.67 | 710998.71 | 45 |
| Assessment Score | -0.27 | 6.972 | 45 |
| Damage Omission Errors - Round 1 | 42.49 | 87.482 | 45 |
| Demand Omission Errors - Round 1 | 128.89 | 140.971 | 45 |
| Demand Commission Error Rate - Round 1 | 0.1297 | 0.06033 | 45 |
| Damage Commission Error Rate - Round 1 | 0.1080 | 0.11230 | 45 |
| Damage Omission Errors - Round 2 | 44.31 | 132.152 | 45 |
| Demand Omission Errors - Round 2 | 73.38 | 93.201 | 45 |
| Demand Commission Error Rate - Round 2 | 0.1305 | 0.06857 | 45 |
| Damage Commission Error Rate - Round 2 | 0.0841 | 0.10808 | 45 |
| Mental Demand - Round 1 | 7.96 | 4.815 | 45 |
| Physical Demand - Round 1 | 3.36 | 4.432 | 45 |
| Temporal Demand - Round 1 | 7.82 | 4.792 | 45 |
| Performance - Round 1 | 6.18 | 4.417 | 45 |
| Effort - Round 1 | 8.20 | 5.190 | 45 |
| Frustration - Round 1 | 4.84 | 5.187 | 45 |
| Composite Score - Round 1 | 38.36 | 20.742 | 45 |
| Mental Demand - Round 2 | 7.18 | 5.301 | 45 |
| Physical Demand - Round 2 | 3.76 | 4.528 | 45 |
| Temporal Demand - Round 2 | 7.02 | 4.464 | 45 |
| Performance - Round 2 | 6.38 | 5.118 | 45 |
| Effort - Round 2 | 7.00 | 5.209 | 45 |
| Frustration - Round 2 | 4.69 | 5.204 | 45 |
| Composite Score - Round 2 | 36.02 | 22.346 | 45 |
| Reaction Time - Round 1 | 9.7179 | 7.31261 | 45 |
| Reaction Time - Round 2 | 8.0075 | 6.50171 | 45 |

Table D-15

*Repair Cost RTM Delta Multiple Regression Descriptive Statistics for Automation Type – No Decision Automation*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Repair Cost RTM Delta | 142333.33 | 562990.81 | 45 |
| Assessment Score | 1.29 | 4.985 | 45 |
| Damage Omission Errors - Round 1 | 114.09 | 136.289 | 45 |
| Demand Omission Errors - Round 1 | 298.58 | 182.621 | 45 |
| Demand Commission Error Rate - Round 1 | 0.2213 | 0.06845 | 45 |
| Damage Commission Error Rate - Round 1 | 0.1438 | 0.10453 | 45 |
| Damage Omission Errors - Round 2 | 103.67 | 207.402 | 45 |
| Demand Omission Errors - Round 2 | 198.64 | 170.854 | 45 |
| Demand Commission Error Rate - Round 2 | 0.1664 | 0.07384 | 45 |
| Damage Commission Error Rate - Round 2 | 0.0859 | 0.08263 | 45 |
| Mental Demand - Round 1 | 10.13 | 5.016 | 45 |
| Physical Demand - Round 1 | 2.87 | 4.181 | 45 |
| Temporal Demand - Round 1 | 7.93 | 4.387 | 45 |
| Performance - Round 1 | 9.49 | 5.168 | 45 |
| Effort - Round 1 | 9.98 | 5.224 | 45 |
| Frustration - Round 1 | 7.16 | 5.681 | 45 |
| Composite Score - Round 1 | 47.56 | 18.743 | 45 |
| Mental Demand - Round 2 | 8.49 | 5.208 | 45 |
| Physical Demand - Round 2 | 2.73 | 3.762 | 45 |
| Temporal Demand - Round 2 | 6.47 | 4.304 | 45 |
| Performance - Round 2 | 7.29 | 5.111 | 45 |
| Effort - Round 2 | 8.91 | 4.917 | 45 |
| Frustration - Round 2 | 5.44 | 5.307 | 45 |
| Composite Score - Round 2 | 39.33 | 19.676 | 45 |
| Reaction Time - Round 1 | 7.5613 | 4.68324 | 45 |
| Reaction Time - Round 2 | 6.0238 | 4.83670 | 45 |

Table D-16

*Repair Cost RTM Delta Multiple Regression Descriptive Statistics for Display Type –Configural*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Repair Cost RTM Delta | 185100.00 | 393764.82 | 30 |
| Assessment Score | 2.00 | 5.363 | 30 |
| Damage Omission Errors - Round 1 | 72.10 | 103.846 | 30 |
| Demand Omission Errors - Round 1 | 218.67 | 173.148 | 30 |
| Demand Commission Error Rate - Round 1 | 0.1721 | 0.07473 | 30 |
| Damage Commission Error Rate - Round 1 | 0.1252 | 0.09753 | 30 |
| Damage Omission Errors - Round 2 | 53.47 | 116.381 | 30 |
| Demand Omission Errors - Round 2 | 147.90 | 160.520 | 30 |
| Demand Commission Error Rate - Round 2 | 0.1682 | 0.07757 | 30 |
| Damage Commission Error Rate - Round 2 | 0.0822 | 0.08394 | 30 |
| Mental Demand - Round 1 | 8.93 | 4.891 | 30 |
| Physical Demand - Round 1 | 2.23 | 3.256 | 30 |
| Temporal Demand - Round 1 | 7.97 | 3.643 | 30 |
| Performance - Round 1 | 8.27 | 4.578 | 30 |
| Effort - Round 1 | 9.53 | 4.681 | 30 |
| Frustration - Round 1 | 6.23 | 5.525 | 30 |
| Composite Score - Round 1 | 43.17 | 17.215 | 30 |
| Mental Demand - Round 2 | 8.60 | 4.861 | 30 |
| Physical Demand - Round 2 | 2.83 | 3.815 | 30 |
| Temporal Demand - Round 2 | 6.90 | 3.670 | 30 |
| Performance - Round 2 | 6.93 | 5.401 | 30 |
| Effort - Round 2 | 8.27 | 4.571 | 30 |
| Frustration - Round 2 | 4.97 | 5.301 | 30 |
| Composite Score - Round 2 | 38.50 | 18.977 | 30 |
| Reaction Time - Round 1 | 7.8460 | 4.64891 | 30 |
| Reaction Time - Round 2 | 6.2493 | 5.11013 | 30 |

Table D-17

*Repair Cost RTM Delta Multiple Regression Descriptive Statistics for Display Type – Separable*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Repair Cost RTM Delta | 323850.00 | 537361.96 | 30 |
| Assessment Score | 0.53 | 6.564 | 30 |
| Damage Omission Errors - Round 1 | 59.63 | 100.037 | 30 |
| Demand Omission Errors - Round 1 | 249.10 | 210.189 | 30 |
| Demand Commission Error Rate - Round 1 | 0.1959 | 0.08906 | 30 |
| Damage Commission Error Rate - Round 1 | 0.1258 | 0.10925 | 30 |
| Damage Omission Errors - Round 2 | 58.27 | 112.377 | 30 |
| Demand Omission Errors - Round 2 | 174.57 | 168.615 | 30 |
| Demand Commission Error Rate - Round 2 | 0.1524 | 0.07742 | 30 |
| Damage Commission Error Rate - Round 2 | 0.0949 | 0.08885 | 30 |
| Mental Demand - Round 1 | 9.97 | 4.824 | 30 |
| Physical Demand - Round 1 | 3.57 | 5.001 | 30 |
| Temporal Demand - Round 1 | 8.03 | 5.055 | 30 |
| Performance - Round 1 | 8.17 | 4.921 | 30 |
| Effort - Round 1 | 9.40 | 5.110 | 30 |
| Frustration - Round 1 | 7.17 | 5.509 | 30 |
| Composite Score - Round 1 | 46.30 | 20.844 | 30 |
| Mental Demand - Round 2 | 8.60 | 5.143 | 30 |
| Physical Demand - Round 2 | 3.13 | 4.305 | 30 |
| Temporal Demand - Round 2 | 7.23 | 4.360 | 30 |
| Performance - Round 2 | 8.33 | 4.936 | 30 |
| Effort - Round 2 | 8.60 | 5.001 | 30 |
| Frustration - Round 2 | 7.23 | 5.975 | 30 |
| Composite Score - Round 2 | 43.13 | 22.771 | 30 |
| Reaction Time - Round 1 | 10.6584 | 6.47919 | 30 |
| Reaction Time - Round 2 | 7.8639 | 5.60116 | 30 |

Table D-18

*Repair Cost RTM Delta Multiple Regression Descriptive Statistics for Display Type – Sematic-Spatial*

| Variable | Mean | Std. Deviation | N |
|---|---|---|---|
| Repair Cost RTM Delta | 357525.00 | 923800.20 | 30 |
| Assessment Score | -1.00 | 6.069 | 30 |
| Damage Omission Errors - Round 1 | 103.13 | 148.128 | 30 |
| Demand Omission Errors - Round 1 | 173.43 | 161.039 | 30 |
| Demand Commission Error Rate - Round 1 | 0.1585 | 0.06986 | 30 |
| Damage Commission Error Rate - Round 1 | 0.1266 | 0.12351 | 30 |
| Damage Omission Errors - Round 2 | 110.23 | 257.434 | 30 |
| Demand Omission Errors - Round 2 | 85.57 | 105.498 | 30 |
| Demand Commission Error Rate - Round 2 | 0.1247 | 0.05819 | 30 |
| Damage Commission Error Rate - Round 2 | 0.0779 | 0.11394 | 30 |
| Mental Demand - Round 1 | 8.23 | 5.315 | 30 |
| Physical Demand - Round 1 | 3.53 | 4.439 | 30 |
| Temporal Demand - Round 1 | 7.63 | 5.014 | 30 |
| Performance - Round 1 | 7.07 | 5.705 | 30 |
| Effort - Round 1 | 8.33 | 5.985 | 30 |
| Frustration - Round 1 | 4.60 | 5.437 | 30 |
| Composite Score - Round 1 | 39.40 | 22.269 | 30 |
| Mental Demand - Round 2 | 6.30 | 5.603 | 30 |
| Physical Demand - Round 2 | 3.77 | 4.454 | 30 |
| Temporal Demand - Round 2 | 6.10 | 5.040 | 30 |
| Performance - Round 2 | 5.23 | 4.636 | 30 |
| Effort - Round 2 | 7.00 | 5.772 | 30 |
| Frustration - Round 2 | 3.00 | 3.343 | 30 |
| Composite Score - Round 2 | 31.40 | 20.065 | 30 |
| Reaction Time - Round 1 | 7.4144 | 6.92868 | 30 |
| Reaction Time - Round 2 | 6.9337 | 6.62111 | 30 |

## Appendix E

Confirmation of permission to use the general design of an online nuclear power plant simulator.

Mike Hurlburt <mike@mikehurlburt.com> 5/18/16

to me

Sorry to take so long getting back to you. But, yes, you can use the general layout of my simulation. If you do cite my design, don't forget the newer version is not fully functional so referring to it might confuse people who expect it to actually work fully.
Thank,
Mike

-------- Original Message --------
Subject: Re: Nuclear Power Plant Simulator
From: Brian Fitch <fitc0019@umn.edu>
Date: Sun, May 01, 2016 1:15 pm
To: Mike Hurlburt <mike@mikehurlburt.com>

Mike,
Thanks for the response. I like the new simulator, the design is more complex but I think the animations and layout will help users understand the relationships between the different components. The animations look good too, I'm impressed.
I'll be interested to see it when it is finished.

To give you a little more background at what I am researching, I'm looking at how changes in how information about the system's status is designed changes the operators understanding of how the system works. For instance, in one of my conditions I will only give them the numeric readouts without the aid of the green/yellow/red bars. The next condition I will add the r/y/g bars, and the next the automation will provide written instructions on which buttons to push. I'll then test them on their understanding of the relationship between component a & b (e.g. the reactor core and the heat ex-changer) and so on.

I was planning on writing the app as a .Net winform, and with your permission use a similar layout and similar logic that dictates the functionality of the system of your first Nuclear Power Plant simulator. I think it is the right degree of complexity for the amount of time people will have to try and learn how it works.

Is it alright if I make a similar system if I cite you and your website as the inspiration for the design?

Thanks again,
Brian

On Sat, Apr 30, 2016 at 10:39 AM, Mike Hurlburt <mike@mikehurlburt.com> wrote:
Hi Brian:
Interesting. Take a look at this.
http://www.mikehurlburt.com/nps2/nps2.php
I am in the process of building version II of NuclearPowerSimulator. This version uses HTML 5's new Canvas specification to produce the animation. The idea is to make the simulator more visual in addition to the numeric readouts. Most of the control functions use JavaScript. Let me know what you think.

-------- Original Message --------
Subject: Nuclear Power Plant Simulator
From: Brian Fitch <fitc0019@umn.edu>
Date: Tue, April 12, 2016 8:31 pm
To: mike@mikehurlburt.com

Hi Mike,

I hope you don't mind me contacting you, but I couldn't locate any contact information on your www.nuclearpowersimulator.com so I found your contact information through the domain registration.

I'm a human factors PhD student at the University of Minnesota, focusing on the impacts of automation design on the human operator. I found your nuclear power plant simulator online and thought it was really great and very close to what I was looking for. With your permission I'd like to use it or something conceptually similar in my dissertation, which I will be starting in the fall.

Ideally I would like to use and modify the code you have, but I completely understand if that is not feasible. I'm willing to recreate it into another program, but saw your copyright and wanted to get your permission first, even to make something conceptually similar.

This is purely an academic project and I would never charge or make money off of the program, and I would of course site your program if I use your code, or cite you and your site as the inspiration for the design if you prefer. I also understand if you don't agree to me using the design in any form.

Thank you for your time,
Brian Fitch