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Effect of Automation Level on Cognitive Workload when Collaborating with a Robotic Assistant

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EFFECT OF AUTOMATION LEVEL ON COGNITIVE WORKLOAD WHEN COLLABORATING WITH A ROBOTIC ASSISTANT

A Thesis

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A.M.D.G.

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Abstract

Manufacturing robotics have been used for decades to perform repetitive tasks, or tasks that require increased levels of speed, strength, or precision to meet production and specification requirements. Determining the appropriate degree of automation for both the human and robot collaborative team members is critical to optimize production as well as user experience. If the degree of automation is too high, the human will be out of the loop which can result in the loss of situational awareness and be detrimental to intervention time and accuracy. If the degree of automation is too low, then the human may experience greater than necessary cognitive workloads resulting in fatigue.

In this experiment, the human team member performed a typing task while the robot team member performed a pick and place task. The human remained in a supervisory role to the robot's actions. As the degree of automation increased, objective and subjective measurements of the cognitive effect were collected. 30 participants aged 18-44 years were divided between two levels of automation. Group one (n=15) participated in the decision support variation of the experiment. The human team member typed from provided literature while they supervised the Universal Robot performing a pick and place task. The robot then initiated movement to pick up the object when the human pressed a button. Group two participated in the automatic execution variation of the experiment in which the robot executed all movements automatically, without input from the human operator. The robot performed the pick task when an object was detected by a photelectric switch. In each scenario, an error was presented on the 5th, 9th, 15th, and 19th production cycle requiring the human to intervene. Time measurements were collected at this juncture to determine how the human reacted to an unexpected situation at each level of automation.

The Subjective Workload Assessment Technique (SWAT) (Luximon & Goonetilleke, 2001) was used to measure the perceived cognitive workload for each participant. Time data were collected for the production cycle and intervention. Typed words per minute were collected and compared to each participant's control. *T*-tests were used to analyze the mean time within groups comparing the control words per minute to the treatment words per minute. Additionally, *t*-tests were used to analyze mean time between groups in the following areas, time to complete twenty cycles, intervention time, and words per minute.

Two hypotheses were developed which results were measured against. The first hypothesis is that the automatic execution operators will be out of the loop while engrossed in the typing task and take more time to notice the error, understand the problem, correct the problem, and return the system to homeostasis than decision support operators. The experiment results did not fully support this hypothesis, but they did reveal that the increased level of automation completed 20 cycles significantly ($p < 0.0001$) faster mean time 9.57 min (SD 0.2×10^{-3}) than the lower level of automation with a mean time 10.25 min SD 0.2×10^{-4}. The second hypothesis is that automatic execution operators

will be faster and more accurate in word processing and have lower subjective workload ratings than decision support operators. This hypothesis was not supported in the experiment results which revealed nearly significant ($p = 0.07$) higher levels of cognitive effort in higher levels of automation (57.5%) than in the lower level of automation (45.3%) (SD 2.0). However, no significant differences were found for word processing time or errors. The results of this study suggest that as automation increases overall production outcomes increase, but so does mental workload. This may help researchers and automation designers understand the relationship between cognitive workload, performance, and levels of automation within a human robotic collaborative team (HRC).

1. Introduction

In industrial environments where automation is utilized, a relationship exists between the robot and its human counterpart. Together, these entities are referred to as a Human Robot Collaborative (HRC) team. Within the HRC team, human-robot interaction occurs both in physical and cognitive contexts (Gualtieri, Rauch, Vidoni, & Matt, 2019). Critical factors associated with the success of automated systems are performance and cognitive workload. These factors may be linked to situational awareness which can be described as one's understanding of their environment and evaluation of actions necessary to operate in homeostasis. A balance must be achieved where the human is not overworked nor underworked to set conditions for the HRC team to be successful. The human must be able to remain in the loop and intervene accurately during normally automated processes. Understanding the inverse relationship between increasing degrees of automation and situational awareness is often referred to as the automation conundrum (Endsley, 2017). More research is needed in this area to gain a better understanding of the automation conundrum and enable designers to allocate tasks in a way that promotes a collaborative and synchronous relationship within members of the HRC team.

This experiment measured cognitive workload as the level of automation increased from decision support to automatic execution. The human operator supervised a robotic assistant performing a pick and place task while the human performed a primary typing task. The system encountered errors on the 5^{th}, 9^{th}, 15^{th}, and 19^{th} cycle, after the human became engrossed in the typing task, simulating an out of the loop scenario. Cognitive performance was measured by collecting time data related to the human's ability to correct the error, as well as their overall production performance. Words per minute data were also compared to each participant's control sample to measure the relative increase in cognitive workload.

The scope and parameters of this experiment can be defined by levels 5 and 7 in Parasuraman's Levels of Automation of Decision and Action Selection. Level 5 is described as when the computer executes a suggestion if the human approves. Level 7 can be described as when the computer executes automatically, then necessarily informs the human (Parasuraman, Sheridan, & Wickens, 2000). These levels of automation were selected because they represent a critical moment in automation design where the human operator becomes less involved in task execution and begins to work out of the loop. The experiment did not explore levels of automation outside of these parameters in the interest of maintaining adequate statistical power and significance given the sample size.

Task allocation is imperative for thoughtful automation design as well as process optimization. Proper task allocation has applications in the industrial environment in fatigue management, accident prevention and task optimization. As designers and researchers strive toward more collaborative relationships within HRC teams, they will seek to understand the factors associated with automation, human performance, and cognitive workloads. This thesis explores how collaboration with a robotic assistant

affects cognitive workloads when increasing automation from decision support to automatic execution.

The results of this study are presented in terms of improved cognitive ergonomic and production outcomes for manufacturing organizations. Applications of the findings may be applied in terms of production time optimization, and mental workload improvement for practitioners interested in implementing human / robot manufacturing teams at the appropriate level of automation.

2. Literature Review

2.1. Automation

Automation support can be defined in multiple ways from task allocation to collaboration. Designers decide which physical or cognitive functions will be executed by robots and which will be executed by their human counterpart. This assignment of roles is the foundation of establishing the human / robot relationship (Chen et al., 2018). Interestingly, collaboration within the human / robot relationship is much more difficult to define. Human robot collaboration (HRC) includes factors such as situational awareness (SA), trust, decision support, and intent (Endsley, 2017).

Early task allocation theories included levels of automation. These served as a starting point for designers and researchers to understand how robots and humans collaborate in a problem-solving environment. Levels of automation are listed with level 10 being the highest where the robot has complete control and makes all decisions outside of human interaction, and level 1 being the lowest where the human makes all decisions and there is no automated assistance (Parasuraman et al., 2000). The information that the robot is asked to analyze can further be organized into five categories: Information acquisition, information analysis, decision selection, action implementation, and adaptive automation (Parasuraman et al., 2000). These categories can aid design and research teams in determining which level of automation is appropriate for the delegation of authority and allocation of tasks. For instance, in a complex environment, information acquisition may be more efficiently executed through a database search while action implementation may require some input from a human decision maker.

Interpreting autonomy in levels of automation, however, separated tasks from members of the HRC team. In modern automation design, tasks are often shared among members of the HRC team. The result of treating automation as graduated levels was empowering one team member rather than building collaborative efforts (Johnson et al., 2014). Subscribing to the levels of automation theory implies an ordinal relationship to the HRC team increasing in autonomy from low to high (Johnson et al., 2011). Recent advances in autonomous systems include several factors which detract from this implication. For example, at the design level, relationship roles must be established. In a given task, the human or the robot may either assume a supervisory role as the initiator of a task, or in a supporting role as the respondent to an action (Johnson et al., 2011). Additionally, team members may take collaborative roles meaning that they both contribute and agree on a decision prior to advancing to a solution (Azhar & Sklar, 2017). Viewing automation as differentiated levels does not accurately address the need to develop collaboration among HRC teams. Subsequent efforts have been applied to incorporating teamwork and enhancing performance among supervisory and supporting members of the HRC team (Bradshaw, Hoffman, Johnson, & Woods, 2013).

Humans and robots can establish interdependent relationships including both independent and dependent roles. While acting in an independent role, an entity can complete a task either with or without the assistance of another entity (Johnson et al., 2011). An example of this is the restart notification on your Personal Computer (PC). The PC may ask the user if they would prefer to restart now or later. No response however will still result in the PC performing a restart. A dependent relationship is the opposite, where input is required from both parties to complete a task. Interdependent relationships can exist outside of supervisory and supporting roles. The theory of soft interdependence builds this relationship by integrating the intent of an entity. This brings HRC teams to a collaborative level where actions are anticipated and build upon each other, enhancing production and user experience (Johnson et al., 2011).

Along with establishing soft interdependencies, the human must develop a level of trust in the automated system, which is the perceived probability that the robot will perform the human's intent to an established standard (Endsley, 2017). To establish trust, both parties should establish situational awareness. Situational awareness (SA) can be described as the human or robot's ability to maintain an understanding of the evolving environment which it is operating in. Understanding the level of SA shared by HRC teams is critical to the effectiveness of the team as a system. A challenge that many designers face is the automation conundrum, meaning that as the level of automation increases, there is an increased probability that the human operator's level of situational awareness will decrease (Endsley, 2017). This could lead to errors if the human is in a supervisory role and required to provide decision making input to further a process.

Research teams are presently exploring coactive design in automation. Coactive design can be described as a system where each member of the HRC team takes an active role in the deconfliction of problem sets to reach an agreed solution. In order for this relationship to be effective, interdependencies must be acutely understood by designers and team members (Johnson et al., 2014).

2.2. Examples of successful HRC implementation

When analyzing an HRC system, the relationship can be assessed based on proximity and time. Depending on the task that the HRC team must address, proximate nature between team members may differ. If the human is required to input information or receive information directly from the robot, close proximity may be required. An example of this may be a robotic assistant that responds to the humans' movements or offers an onboard display. In some cases, however, the robot can share information from a greater distance. An example of this is an unmanned aerial vehicle. Regardless of their proximate relationship, for HRC teams to be successful, they must support their interactions with effective communication. Timing plays a critical part in communication. Timing for a HRC team can best be described as the moments when each member either provide or request information, then provide a response which furthers the process (Azhar & Sklar, 2017).

The aviation and automotive industries have been very successful in implementing automated systems. In these industries, practitioners have developed methods where efforts between human and automated systems are synchronized and collaborative, enhancing both user experience and task performance. Examples of this type of collaboration are evident in autopilot and intelligent drive systems. These systems enhance both the robot and human's ability to operate within an environment and have been successful through systems designed to interpret environmental changes and maintain situational awareness while offering flexibility and adaptability (Antonelli, Astanin, & Bruno, 2016). The relationship shared by the HRC team can then become collaborative in nature.

Similarly, the healthcare industry has implemented the use of social human robot interaction (sHRI). This type of automation has been introduced at the patient interaction level. Patients can interact with robots to orient themselves in the hospital, schedule appointments, and get general information. This model is based on relatability to human counterparts. These systems can communicate with their human counterparts using vocal prompts and natural data input modeling. Careful programming must be applied to these systems to ensure that vocal prompts are understood with a high degree of accuracy. If the human has to repeat themselves too many times, they will get frustrated and lose trust in the system. (Sadrfaridpour, Saeidi, & Wang, 2016). Studies have found that when humans collaborate, rather than supervise robots, levels of trust in the automated system increase (Azhar & Sklar, 2017). While increased levels of trust can positively influence efforts to achieve collaborations among HRC team members, practitioners must caution against over reliance of the automated system (Sadrfaridpour et al., 2016). Conversely, in cases where the human team member distrusts the system, underutilization is often the result (Hancock et al., 2011).

Surprisingly, an example of an area where automation was slow to be embraced is in space exploration. This is an example of an environment where the risk of failure outweighs the benefit of automation. Early Mars rovers had the capability of performing many autonomous functions, however NASA engineers decided to act in prudence and manage individual tasks with teams of operators. This brings to light the reality that individual responsibility cannot be placed upon an automated system the same way that it can a human. Through delegation of authority, humans can be held responsible for both performance and outcomes of the system (Bradshaw et al., 2013).

One of the common implementation errors found in manufacturing is that robotic assistants are often partitioned away from their human collaborator. This is evident in assembly line operations where movement within a confined space may inspire constraints in the name of safety. Similarly, robotic power distribution is often governed to limit force (Pearce, Mutlu, Shah, & Radwin, 2018). While safety assurance is achieved, performance is degraded. This paradigm can be mitigated through automation design. In automation, many design and optimization measurable improvements can be specifically attributed to flexible and adaptable relationships (Weckenborg & Spengler, 2019). While

flexibility is important in automation, being too general can lead to inappropriate levels of regulation (Chen et al., 2018).

2.3. Task Allocation

Researchers have approached the problem of task allocation in multiple ways. Depending on the variables involved, the practitioners may apply different values to performance measures and outcomes. An organization may allocate tasks to automated systems based on where it places the most value during the production cycle. Some organizations may select production-based algorithms which value time as the determining factor, while others may value different factors. In a quality-based model, the determining factor will be accuracy and the time variable may not have a decisive impact on performance measures.

Other task allocation considerations are based on which type of activities each member to the HRC team is best suited to accomplish. Humans are typically better at adaptive motor adjustments and compiling variables to make dynamic decisions. Concurrently, robots are best suited at performing strenuous and repetitive functions including those which would require awkward posturing (Pearce et al., 2018). This method of task allocation can be refined by incorporating the Markov decision process or Bayesian inference to predict human behavior or goals (Makrini, Merckaert, Winter, Lefeber, & Vanderborght, 2019).

Once tasks have been allocated between team members, the human must understand their role as supervisor or collaborator. Once roles are established, the human can develop trust in the automated system. This can be achieved through coordination of actions between team members (Admoni, Shah, & Srinivasa, 2017). Increased levels of trust and coordination are required as the cost of failure increases. The human's willingness to utilize robotic assistance is the product of their understanding of roles, their ability to coordinate input and output, as well as the robot's ability to meet their intent (Hancock et al., 2011).

To assign HRC relationship roles at the design level, engineers must understand the associated factors. Some of the most important considerations are value added inputs and outputs including situational awareness, cognitive workload, and trust (Chen et al., 2018). The goal is to establish intuitive processes that enable team members to work toward a common goal. Depending on which team member assumes the supervisory role, decision making authority can be assigned. An important factor for relationship sustainability is that the human maintains a sense of agency throughout the process. This can be accomplished during automation design by providing the human partner opportunities to provide critical information (Kildal, Martín, Ipiña, & Maurtua, 2019). This is particularly useful when the system requires information collected from dynamic sources. Often, a human operator can select and process information that has not been encoded more accurately than their robotic partner (Gombolay, Bair, Huang, & Shah,

2017). An example of this is information derived from past experience or verbal communication.

2.4. Musculoskeletal effects of HRC Implementation

When assigning roles in a HRC team, physical considerations must be considered as well. There are many musculoskeletal advantages to incorporating HRC teams including injury prevention and fatigue management. Private industry employers reported 2.7 million nonfatal workplace injuries and illnesses in 2020 (Bureau of Labor Statistics, 2021). In many cases the risk of practitioners developing musculoskeletal disorders is greatly reduced by incorporating automated systems. Incorporation of these systems has become more relevant as the workforce ages (Makrini et al., 2019). By aligning tasks with team members who are innately advantaged, musculoskeletal disorders and over exertion can be avoided. For example, robots are more equipped than humans to safely execute tasks or actions involving repetitive motions or exact applications of force (Pearce et al., 2018).

Collaborative robotics can provide sustainable solutions for industrialized countries who are at risk of being affected by the plight of work-related musculoskeletal disorders. Collaborative robotics are designed to work with their human counterpart to enhance their abilities. Some examples are joint manipulation, force application and amplification, and inertia guidance. (Maurice, Padois, Measson, & Bidaud, 2017). Ability enhancements such as these not only reduce fatigue, but also reduce the risk of human error in the process (Pearce et al., 2018).

Decisions on how to apply automation to a process should be made with considerations to safety and benefits to the human workers. An effective method should include factors such as force application, posturing, ergonomic benefits, human movement capability, and the optimal assembly process (Pearce et al., 2018). Often efforts are made to limit interaction between robots and humans in a workspace. These efforts include power limitation and physical separation. These decisions are rooted in extreme risk aversion and task allocation. In this method of automation integration HRC team members tend to coexist in space and effort rather than achieve their designed intent, which is collaboration (Kim, Lorenzini, Balatti, Wu, & Ajoudani, 2019). Designers and engineers work to ensure that workspaces are shared in a collaborative manner rather than exercising replacement methods. Collaboration is often captured where physical and cognitive ergonomics are combined. Robots assist humans in factors such as force management and repeatability, and humans apply skills such as dynamic decision making, creativity, and variable management (Gualtieri et al., 2019).

2.5. Cognitive workload effects from HRC implementation

A large part of the automation implementation process is developing an environment where the human counterpart feels confident in employing the robot. The cognitive workload experienced by the human counterpart is an impactful factor in this equation.

Cognitive workload is influenced by factors such as task allocation, stress, trust, situational awareness, and environmental factors. Developing a conducive work environment where the human counterpart feels safe interfacing with the robot is critical to developing trust and acceptance to the platform (Kildal et al., 2019). To compound on this, designers have found that the role the human is assigned has a dramatic effect on cognitive workload. When the human is acting as a collaborator rather than a supervisor, stress levels are significantly lower (Azhar & Sklar, 2017). Stress and cognitive workloads have been linked, however are not parallel. While in some cases, lowering stress may increase cognitive capacity and performance, the inverse may be true if too much stress is removed. By removing too much stress, situational awareness will decrease resulting in decreased performance (Gombolay et al., 2017).

Automated decision support is one way that designers strive to build HRC teams while maintaining situational awareness. Automated decision support describes a familiar function where a limited menu of options is presented to the human operator to aid in their decision making and further a process toward a solution. The robot calculates a variable and presents options to the human. While designers and engineers attempt to predict appropriate responses based upon probability, analysis by the human operator is required to select the most viable option. While benefits include increased accuracy and user experience, the potential for negative effects including automation bias and attention withdrawal exist.

When decision authorities are passed from human to robot, or conversely from robot to human, a situational awareness gap often presents itself. The more robust the automation, the more out of the loop the human may be. In this case the human will suffer from a loss of situational awareness and be more likely to struggle with decision making or commit errors when authority is transferred to them. Conversely, increasing the cognitive workload applied to the human over time will increase stress and fatigue which in turn can have similar effects. This is called the automation conundrum (Endsley, 2017). This illustrates the delicate balance that designers must consider when creating collaborative systems.

Humans respond more positively when operating in the loop rather than out of the loop. When operating out of the loop, a human will need to regain situational awareness prior to providing input. The time that the human spends gathering information in this situation does not add value to the process. When operating in the loop however, the human is actively engaged and processing critical data as it becomes available. This allows the human to make more accurate and timely decisions, adding value to the HRC team and the process. Additionally, humans retain information more accurately when the data is presented in real time, building on their ability to learn from the experience (Endsley, 2017).

There is often a tradeoff of positive and negative cognitive effects when applying automation to a process. Too much or too little automation can have negative effects of

the humans' ability to accurately intervene or assume decision making authority. The robustness of automation applied can be either outcome or process driven (Gombolay et al., 2017). Optimal levels of automation can be established though through experimentation. As data is aggregated, it can be displayed as a normal distribution with automation along the X axis and situational awareness along the Y axis (Endsley, 2017) as depicted in (Figure 1).

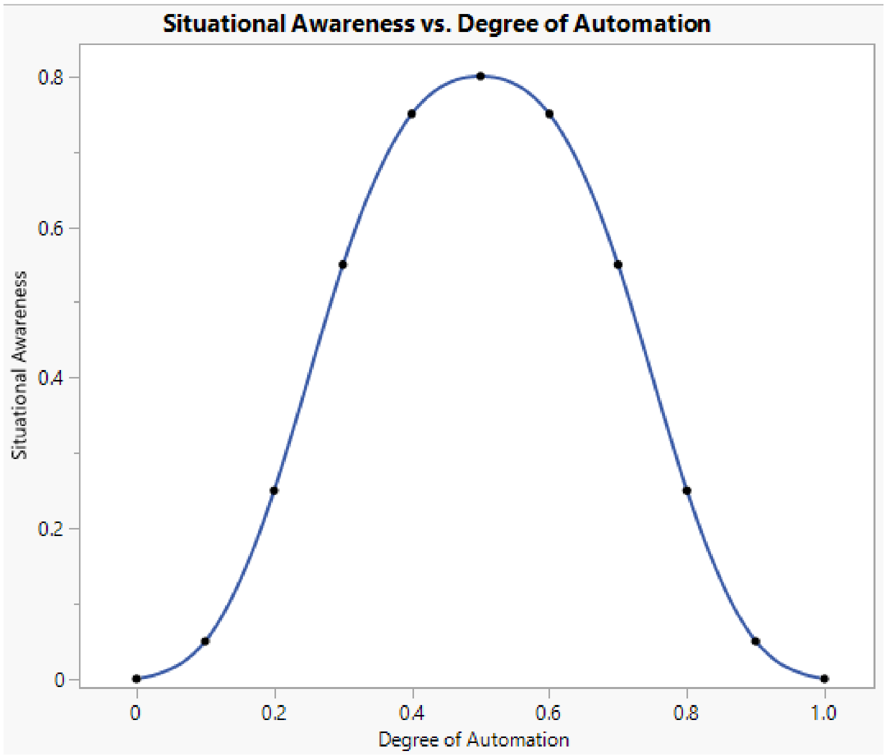

Figure 1. Situational Awareness Automation Relationship

2.6. Production and financial effects related to HRC implementation

From a manufacturing perspective, there is a managerial strategy to automate as much as possible. This decision is not without its own pitfalls though. Inevitably there will be processes that are too complex, nuanced, or expensive to automate. These are the tasks that an out of the loop human operator will be charged with (Parasuraman et al., 2000). This does not lead to sustainability within a process. In this process the human will suffer from errors and fatigue, and ultimately detract from optimization of the process. A more sustainable approach is to design automation based upon the collaboration of human and machine where each of their efforts enhance each other's capabilities.

In small scale manufacturing settings, manual operations may be preferred over automation to accomplish tasks such as construction, bin loading, and inspection. In large scale operations the benefits of automating these tasks are rapidly realized (Antonelli et al., 2016). This is directly related to economies of scale, meaning that the cost of

acquisition and implementation can be recovered through the production and sale of increased units.

The cost of acquisition, implementation, and maintenance always serves as a barrier that decision makers must overcome when making automation decisions (Antonelli et al., 2016). Consider the following automation scenarios which are illustrated by (Figure 2); fully automatic, collaborative, and fully manual. In the fully automatic scenario, there is a complex implementation process. Once the system has been implemented though, it is easy to initiate production. Task completion times may be optimized barring nuanced instances where humans must intervene. Those instances, however, are unscheduled and take time for the human to understand the variables involved. In the collaborative scenario, initial implementation is much less complex while maintaining fairly quick process initiation. Task completion times for robotic tasks remain optimized while human intervention is more accurate and timelier. Lastly, in the fully manual scenario, there is no implementation time and process initiation is measurably faster. This method leads to fatigue, and non-value-added time in large scale production models though. In these scenarios, the determining factor for automation implementation is batch size (Antonelli et al., 2016).

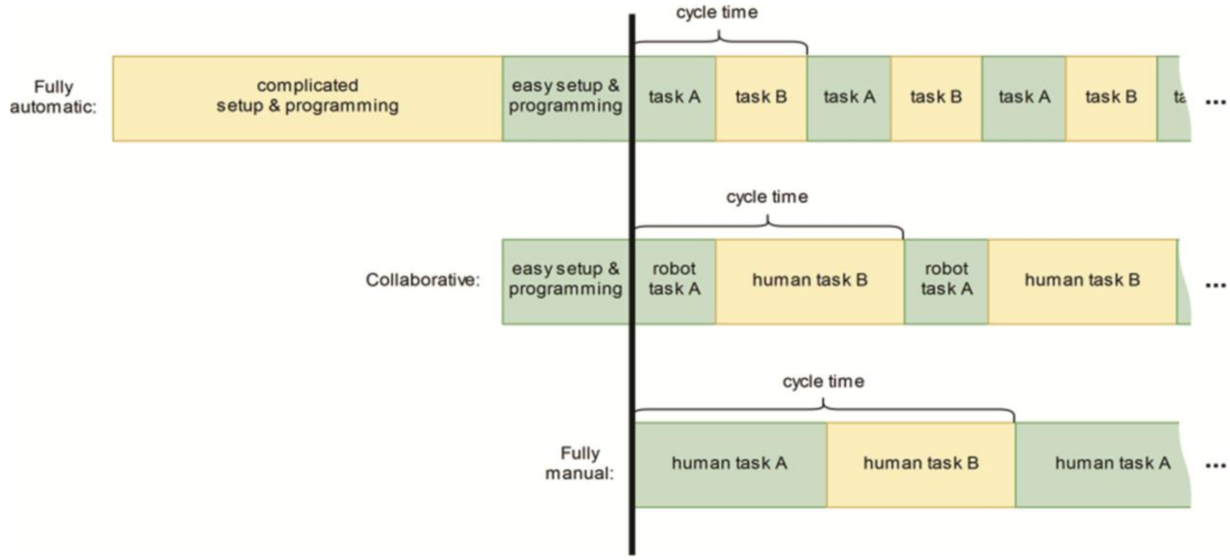

Figure 2. Automation Cycles

(Antonelli et al., 2016)

Finally, managers and system designers must consider the user population. In the testing phase, samples must be selected based on similar age, physical capability, and education level to the intended user. If a system was designed and tested using university students as the sample, but its intended user group includes elderly factory workers, there may be untested variables that could affect its use. The intended audience may have different physical or cognitive needs than the sample if not selected carefully (Gombolay et al.,

2017). Several iterations of field tests and adjustments may be needed for the implementation team to achieve the intended level of optimization.

2.7. Future Work

HRC teams are effective in many industries and in daily life. Degrees of automation can vary depending on the variables involved. The prevailing application of automation is collaboration. What is needed to balance the automation conundrum is further research into the methodology of evaluating the tradeoff between automation, cognitive workload, and situational awareness. A better understanding of the automation conundrum will mitigate the risk of the human or robot being out of the loop when authorities are transferred from one to another. Through this, user experience and safety will improve. Simultaneously, non-value-added time will decrease resulting in increased production value. Further research in this area will enable automation practitioners to make more informed decisions and evaluate realistic optimization scenarios.

3. Methods

3.1. Design of Experiment

This experiment followed a true experimental design and was conducted to measure how collaboration with a robotic assistant affects cognitive workload when increasing automation from decision support to automatic execution. Two test groups consisting of 15 participants each completed a between-subjects trial using either decision support or automatic execution levels of automation. Assignment of the participants was randomized through open enrollment. For both groups, the human acted in a supervisory role to the robotic assistant who was carrying out a pick and place operation. Group one participated in the decision support level of automation, and group two participated in the automatic execution level of automation. While the human performed a typing task, object placement errors were introduced to the automated system, interrupting the operation. The human would then need to notice the error, understand the problem, correct the error, and return the system to normal operation. Measurements were taken including words per minute typed (WPM), errors per minute typed (EPM), object placement error intervention time, cycle time, and subjective workload analysis technique (SWAT) results.

Two hypotheses were developed based upon analysis of prior research.

1. Automatic execution operators will be out of the loop while engrossed in the typing task and take more time to notice the error, understand the problem, correct the problem, and return the system to homeostasis than decision support operators.
2. Automatic execution operators will be faster and more accurate in word processing and have lower subjective workload ratings than decision support operators.

3.2. Independent Variable

One independent variable was applied to this study: automation level, by increasing the degree of automation from decision support to automatic execution. Group one (decision support) participants used a button to signal the robot to initiate motion to pick up an object in the target area. Group two supervised the automatic execution of the pick and place activity. During the automatic execution portion of the exercise, a photoelectric switch signaled the robot to initiate necessary movement once the object entered the target area.

3.3. Dependent Variables

Five dependent variables were measured in this experiment: production speed, intervention speed, perceived cognitive effort, words per minute typed, and degree of accuracy

1. Production Speed (s): The process was timed from the moment that the investigator announced “begin” until the moment that the robot has placed the object down on the twentieth cycle.

2. Intervention Speed (s): Time data were collected beginning at the moment the object touched the table outside of the target area, causing a cycle error which needed to be corrected by the human team member and ending at the moment that participant resumed typing at their workstation.
3. Perceived Cognitive Effort: Data were collected using the Subjective Workload Assessment Technique (SWAT) (Luximon & Goonetilleke, 2001). This data is subjective and measures workload in three different dimensions, time load, mental effort load, and stress load. This serves as an indicator of perceived cognitive effort and user experience.
4. Words Per Minute Typed: As a measurement of cognitive workload, participants' words per minute typed were captured. Participants were instructed to type as quickly and accurately as possible without retuning to make corrections. They typed from the provided literature (a textbook) for three minutes to capture their control words per minute. Participants' words per minute were captured during the trial as they supervised the pick and place activity. The difference between the initial and trial speeds served as a measure of their cognitive workload. Microsoft Word was used as the medium for word processing. Time was measured using a stopwatch operated by the investigator. Data collection was initiated when the investigator provided the verbal prompt "begin" and commenced upon completion of the time elapsed for the control sessions or the completion of the final cycle during treatment sessions.
5. Degree of Accuracy: In Microsoft Word, spelling errors within a document can be quantified by selecting the editor function within the review tab. Spelling errors were counted and annotated at the end of each session indicating a degree of accuracy.

3.4. Universal Robot

The robot assistant used for this experiment is a Universal Robots UR5e (Figure 3). Universal Robots is an international company headquartered in Odense, Denmark. The UR5e is designed to work in close proximity to human HRC team members by utilizing safe stop technology. A gripper end effector was attached to enable the robot to perform the pick and place task. The UR5e is capable of managing payloads up to 5kg / 11 lbs. ("Universal Robots," 2022), however, in this application the objects are much smaller than the specified threshold as depicted in (Figure 4) and (Figure 5).

Figure 3. UR5e

("Universal Robots," 2022)

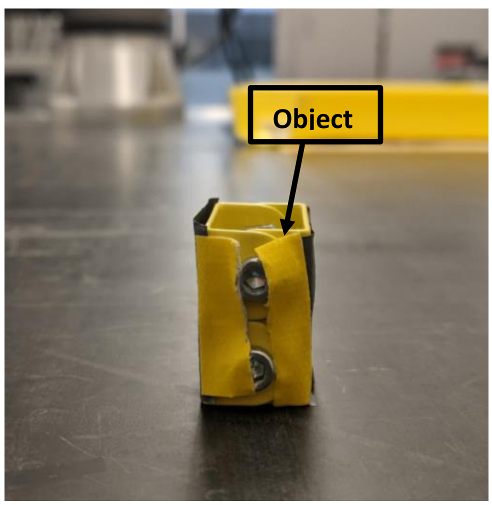

Figure 4. Object View 1

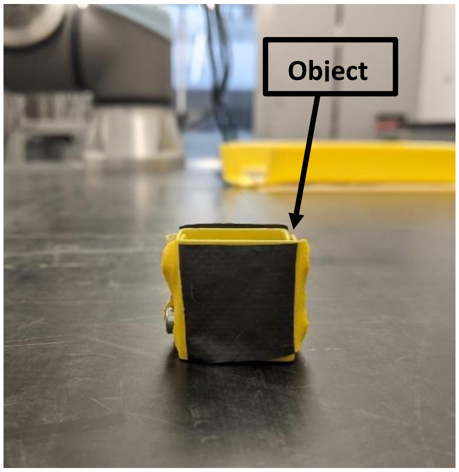

Figure 5. Object View 2

3.5. Experiment Layout

The experiment was conducted at Louisiana State University, Patrick F. Taylor Hall, Room 2352, in Baton Rouge, Louisiana. The participants were provided a workstation with a clear view of the robotic assistant's work area positioned 72 inches away from the target area when measured from the center of the keyboard (Figure 6). The participant's work area included a laptop, keyboard, mouse, button, text support stand, and text (Figure 7). The robotic assistant's work area consisted of the UR5e robotic arm, gripper end effector, target area, photoelectric switch, retroreflector, and bin (Figures 8 and 9).

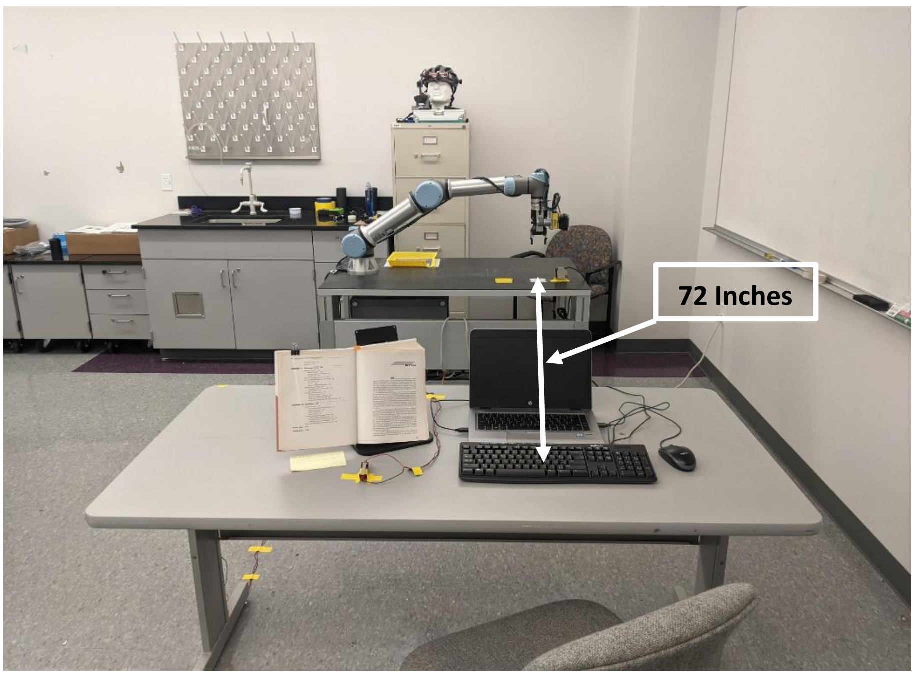

Figure 6. Overview of the Experiment Area

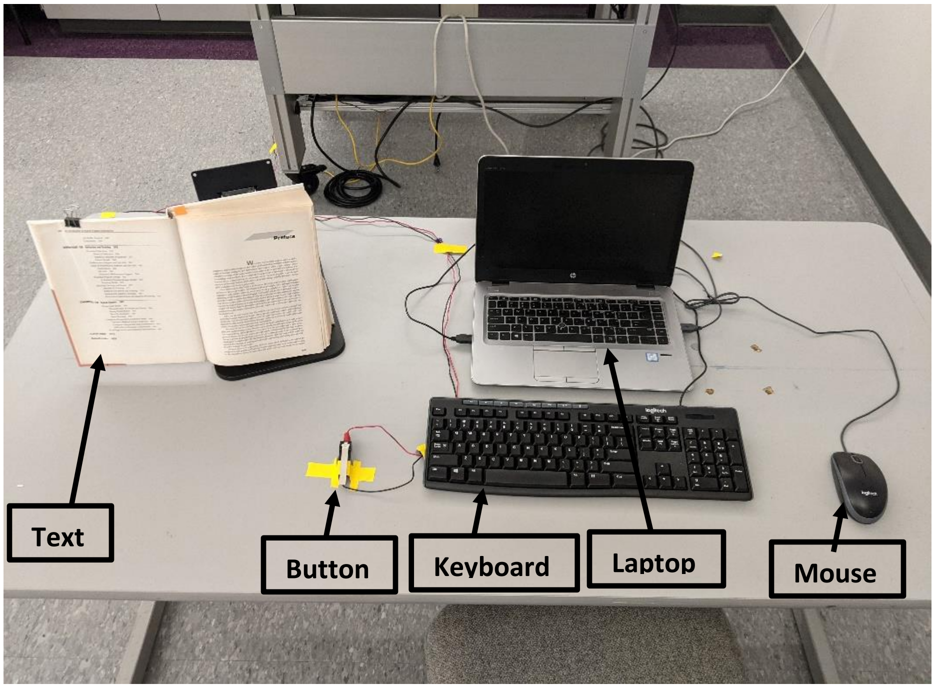

Figure 7. Participant's Station Layout

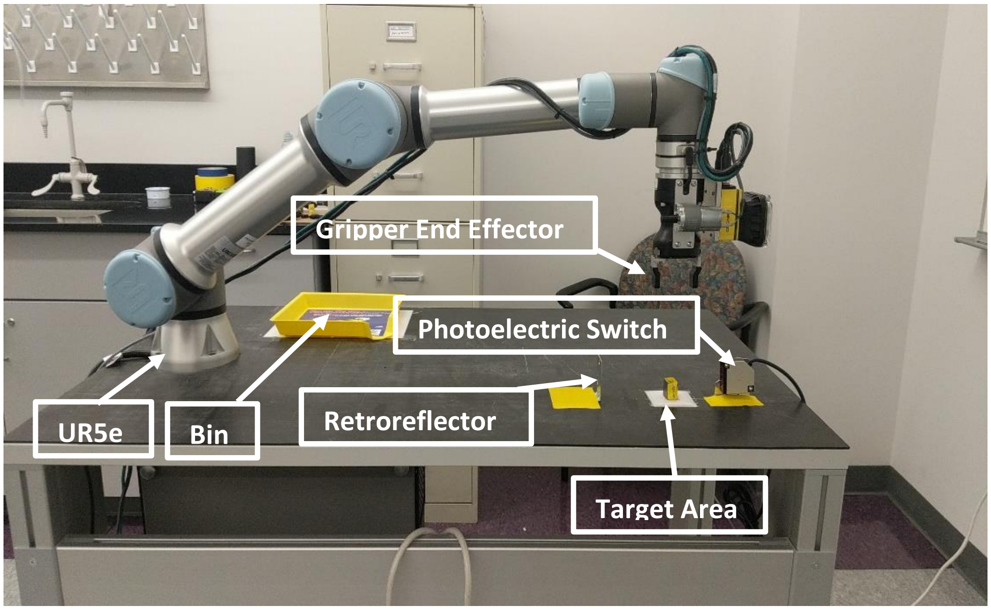

Figure 8. Robotic Assistant’s Workspace

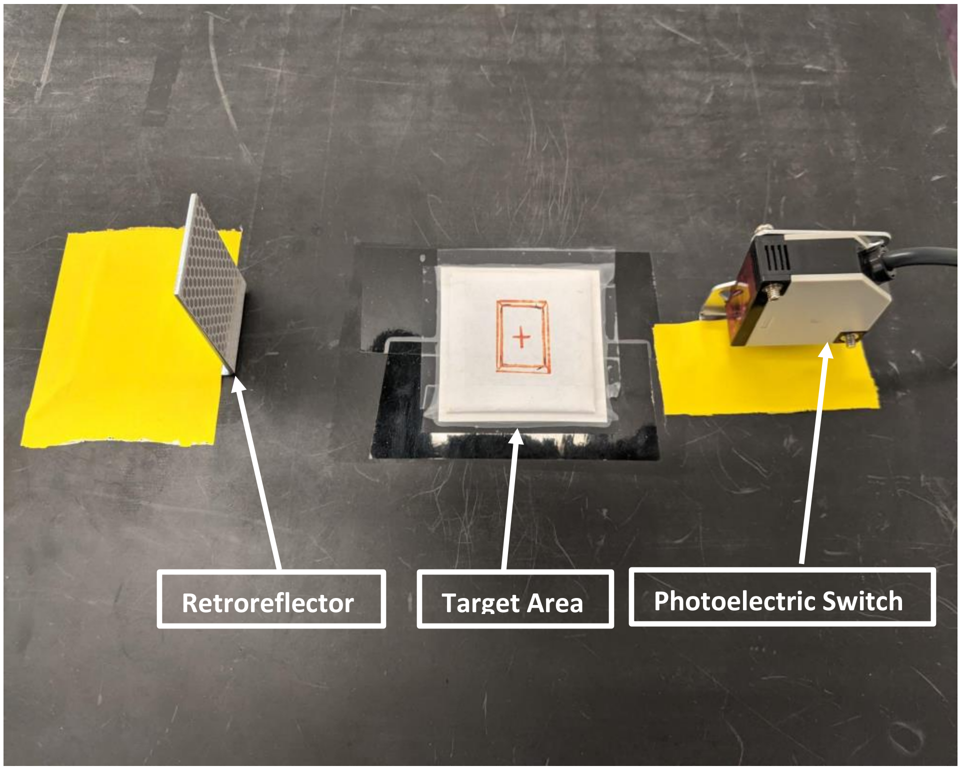

Figure 9. Layout of the Photoelectric Switch and Target Area

3.6. Subjective Workload Assessment Technique (SWAT)

The Subjective Workload Assessment Technique (SWAT) is a measurement tool used to quantify perceived subjective values associated within three dimensions, time load, mental effort load, and stress load (Appendix A). After the treatment iteration of the experiment, each participant rated their interpretation of the dimensions. The participant placed a mark along the 10-inch line representing each dimension. The investigator then measured the placement of the mark and from the point of origin at the far left of each dimension. The mark was then represented as a percentage ranging from 0%-100%. As the value of the percentage increases the perceived cognitive workload increases.

3.7. Task

Typing Task: Each participant was provided with content from a textbook, An Introduction to Human Factors Engineering (Wickens et al., 1997). The text was provided via hard copy and propped up on a stand for their comfort. The word count was displayed at the lower left side of the screen and time was kept on a stopwatch operated by the investigator. Participants were provided the opportunity to adjust the location of the text, keyboard, mouse, and chair according to their comfort. Participants were allowed to make physical adjustments and practice typing. The control typing task literature began with the first word of the preface and continued until three minutes elapsed. The trial typing task

literature began with the first word of chapter one and continued until all twenty cycles of the robot pick and place task are complete. Once the control and trial were initiated, the participant was not allowed to stop or take a break. A break was provided between the practice, control, and trial tasks.

Decision Support Task: The participant was provided with a button that when pressed would signal the robot to initiate the pick task. The pick task began with the downward movement of the robot arm toward the object and culminated when the gripper end effector completed its grasp of the object. The participant was instructed that the button should be pressed when the object is placed in the marked target area and the robotic arm was in position to initiate the pick task. The participant was given an opportunity to practice the task and to ask questions of the investigator. The button was affixed to the workstation left of the keyboard.

Automatic Execution Task: The participant was informed of how the photoelectric switch works. The switch signals the robot to initiate the pick task when the object is placed in the marked target area, interrupting the light beam emitted by the sensor. The participant was given an opportunity to practice and observe the execution of the task and ask the investigator any questions prior to the start of the exercise.

Intervention Task: On the 5^{th}, 9^{th}, 15^{th}, and 19^{th} cycle of the trial task, the object was placed just outside of the marked target area. The participant was briefed during orientation that if this should occur at any time, they need to stand up from their workstation, walk over to the robot assistant’s workspace, place the object back in the marked target area, then continue the trial. The investigator collected time data using a separate stopwatch from the moment the object touched the table outside of the target area to the moment that the participant began typing again at their workstation.

3.8. Data Collection

Prior to data collection, consent forms (Appendix B) were signed by all participants (see Appendix C for IRB approval). Potential human risk was evaluated as being very low. Participant data was kept confidential and only available to the investigator. To achieve randomization, participants were assigned randomly to an experiment group as they register for an opportunity to participate in the experiment.

3.9. Participants

Participants were recruited through students enrolled in any Industrial Engineering course over a one-month period with the instructor’s approval. To achieve a medium to large effect with a two tailed $\alpha = 0.05$ and power = 0.80, using Cohen’s D table, 30 participants were observed. 31 samples were collected with one sample excluded from the results as the participant did not understand the instructions and did not respond to the error when it was presented. 15 males and 15 females participated in the experiment. 7 males and 8 females participated in the decision support treatment aged 18-27 years with a mean age

of 20.7 years. 8 males and 7 females participated in the automatic execution treatment aged 18-44 years with a mean age of 23.9 years. Each session lasted approximately 25 minutes which included orientation, consent, practice, control, and treatment sample collection.

Inclusion criteria included individuals enrolled in any Industrial Engineering Course and above the age of 18. Participants must have corrected or normal vision and have no cognitive disabilities or physical pain that would affect their ability to perform a typing task or correct a placement error in a pick and place activity. If participants did not meet any of these criteria, they were not permitted to participate in the experiment. The inclusion and exclusion criteria were available to the participant in the informed consent form.

3.10. Procedure

Only one participant at a time executed the experiment. Both groups received an orientation of the experiment, the Universal Robot's role, and their workstation. The participants were allowed to make physical adjustments and practice typing. After a break, the participants then provided a three-minute control sample of their typing ability. After a second break, the participants completed the experiment treatment session. The Universal Robot was programmed with either a decision support or automatic execution pick and place task. Simultaneously, the participant typed from the provided literature. The task cycled twenty times. On the 5^{th}, 9^{th}, 15^{th}, and 19^{th} attempt, the object was placed just outside of the target area. This provided an error that the human must intervene and correct prior to completing the task. The work cycle resumed allowing the HRC team to return to a state of normal operations.

Group one participated in the decision support treatment. Execution of the pick task was signaled by a button placed on the participant's workstation to the left of the keyboard. When an object was placed in the target area, the participant pressed the button signaling the robot to pick up the object and place it in an adjacent bin. Group two participated in the automatic execution treatment. The execution of the pick task was signaled by a photoelectric switch adjusted to signal the robot to pick up the object and place it in an adjacent bin when an object entered the target area.

3.11. Analysis

Descriptive statistics were used to illustrate findings. Time and words per minute data are represented in terms of mean and standard deviation for comparison purposes. Visually, this data is represented as a bar chart. Data collected from the SWAT is represented in a bar chart. *T*-tests ($p < .05$) are used to analyze the mean time within groups comparing the control words per minute to the treatment words per minute. Additionally, *t*-tests ($p < .05$) are used to analyze mean time between groups in the following areas, words per minute, errors per minute, error intervention time, cycle time, and SWAT data.

4. Results

4.1. Words Per Minute

Mean decision support words per minute (WPM) of 30.5 (SD 10.1) was significantly lower (p < 0.0001) than the mean control WPM of 35.0 (SD 8.5). Mean automatic execution WPM of 28.1 (SD 6.3) was significantly lower (p < 0.0001) than the mean control WPM 35.0 (SD 8.5) (Figure 10). While the mean WPM 30.5 (SD 10.1) was higher for decision support than the mean WPM for automatic execution 28.1 (SD 6.3) when compared, the two data sets were not significantly different (p = 0.5).

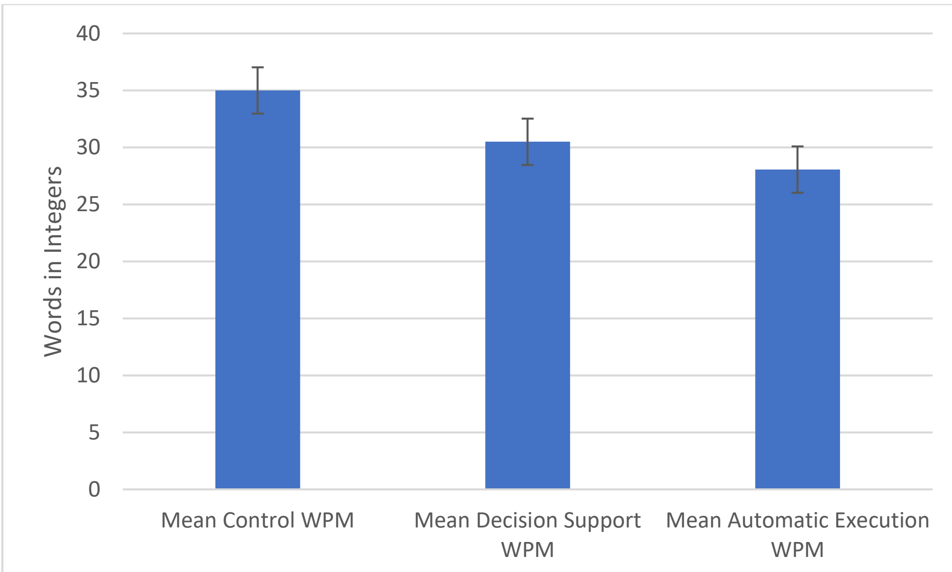

Figure 10. Mean Words Per Minute

4.2. Errors Per Minute

The decision support mean errors per minute (EPM) 1.4 (SD 1.1) was significantly higher (p < 0.0001) by 0.25 EPM than the mean control EPM 1.2 (SD 1.6) (Figure 11). The automatic execution mean EPM 2.0 (SD 1.2) was significantly higher (p < 0.0001) by 0.8 EPM than the mean control EPM. The mean EPM for decision support 1.4 (SD 1.1) was lower than the EPM for automatic execution 2.0 (SD 1.2), however when the treatments were compared, there was not a significant difference (p = 0.3).

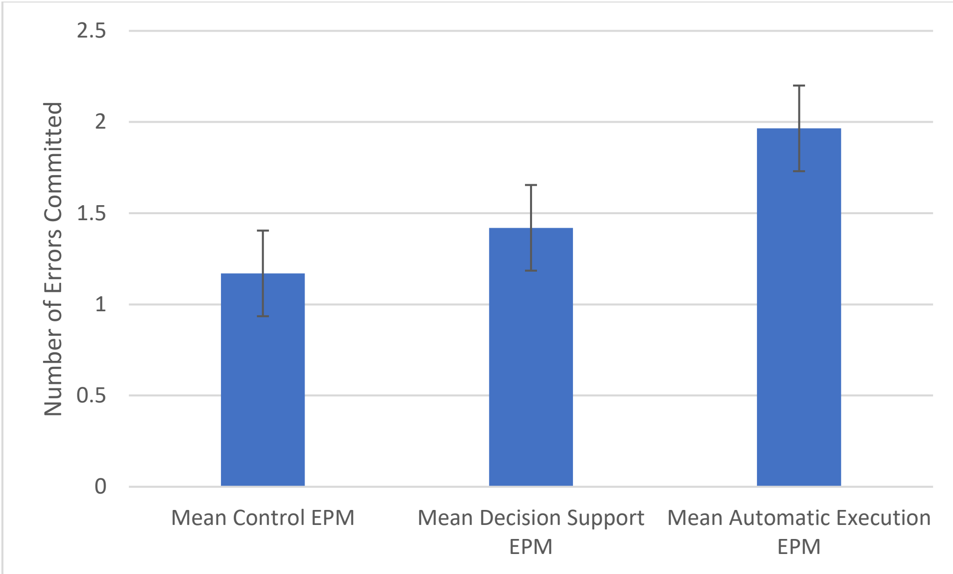

Figure 11. Mean Errors Per Minute

4.3. Error Interventions

Individual intervention data were collected when errors were presented on the 5th, 9th, 15th, and 19th cycle. The mean intervention time to acknowledge the error, correct the error, and the participant return to their workstation were compared in decision support and automatic execution. In the first observation, the mean intervention time for automatic execution 13.5s (SD 4.3×10^{-5}) was not significantly longer (p = 0.7) than the mean intervention time for decision support 12.6s (SD 3.7×10^{-5}). In the second observation, the mean intervention time for automatic execution 12.2s (SD 4.4×10^{-5}) was not significantly longer (p = 0.6) than the mean intervention time for decision support 11.5s (SD 3.5×10^{-5}). In the third observation, the mean intervention time for decision support is now insignificantly (p = 0.5) longer 13.1s (SD 4.0×10^{-5}) than the mean intervention time for automatic execution 12.4s (SD 5.0×10^{-5}). In the fourth observation the mean intervention times are nearly the same but the results were not significantly related to each other (p = 0.8). The decision support mean intervention time for fourth observation was 11.7s (SD 4.0×10^{-5}) while the mean intervention time for the fourth observation in automatic execution was 11.2s (SD 5.0×10^{-5}) (Figure 12). The data for all the decision support and automatic execution intervention times were combined by treatment to explore their combined mean intervention times. The combined decision support mean intervention time was insignificantly lower (p = 0.9) 12.2s (SD 3.7×10^{-5}) than the combined automatic execution mean intervention which was 12.3s (SD 4.3×10^{-5}) (Figure 13).

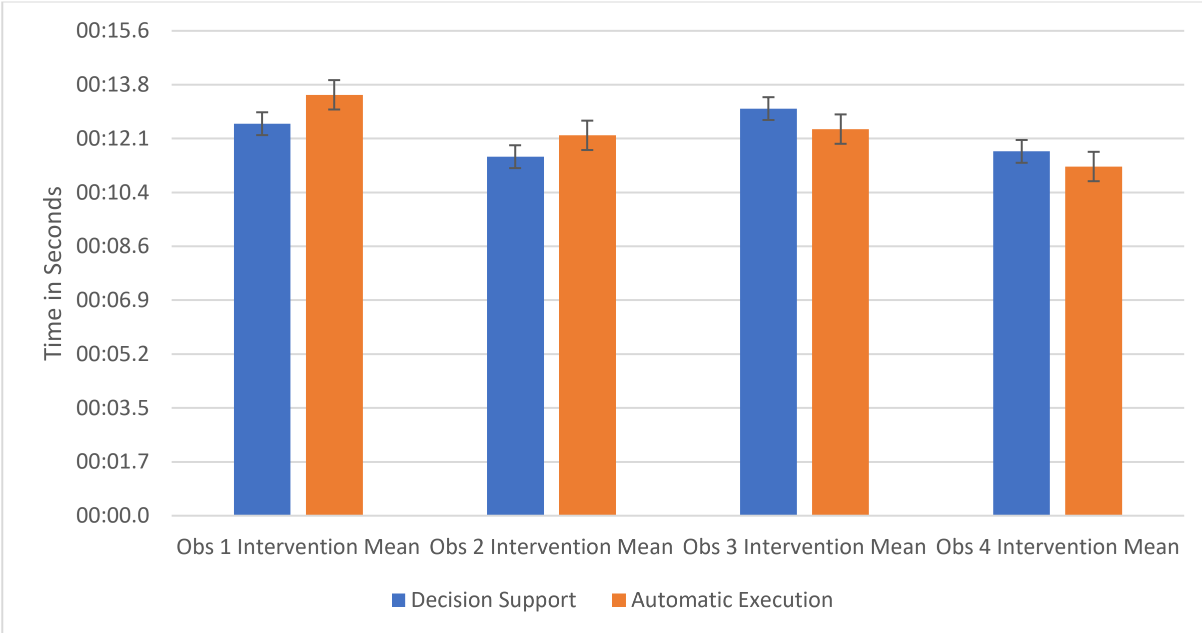

Figure 12. Mean Intervention Time Mean for Individual Observations

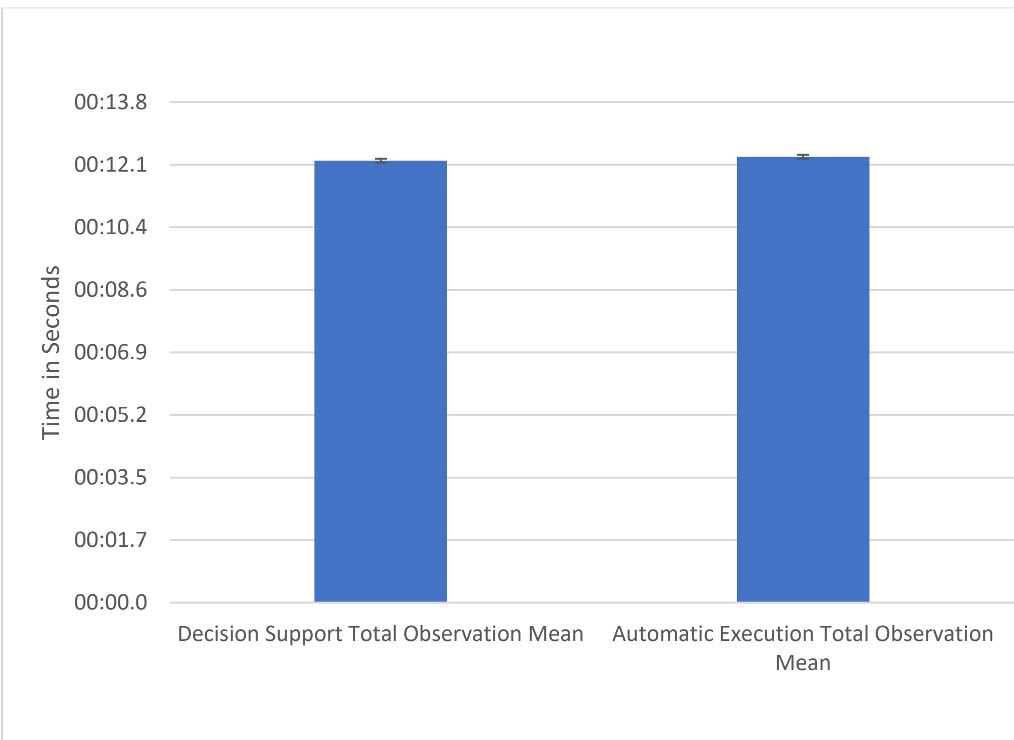

Figure 13. Mean Intervention Time Comparison

4.4. Cycle Time

The decision support mean time to complete 20 cycles was 10.25 min SD 0.2×10^{-4}). The automatic execution mean time to complete 20 cycles was significantly shorter ($p < 0.0001$) with a mean of 9.57 min (SD 0.2×10^{-3}) (Figure 14).

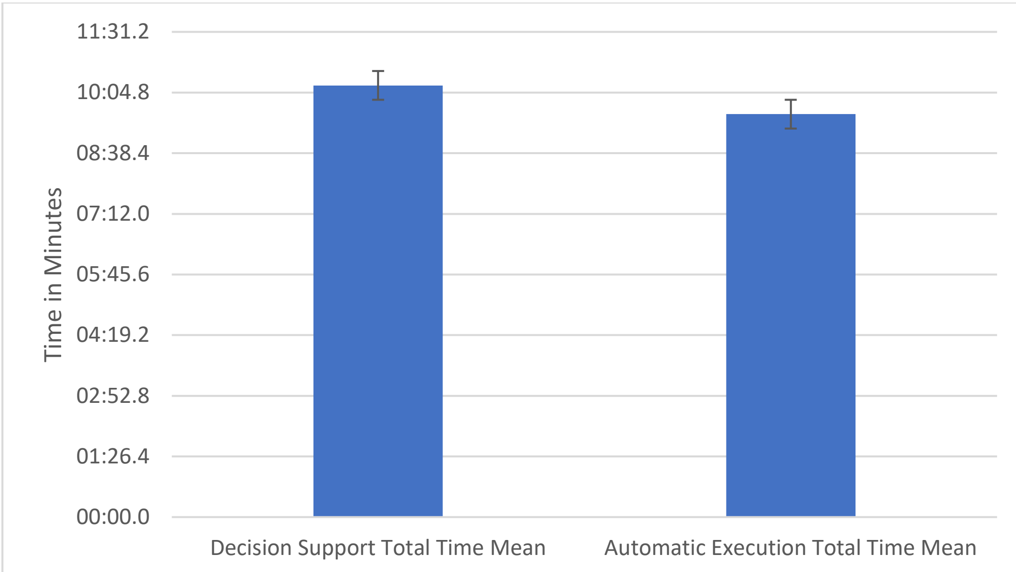

Figure 14. Mean Time to Complete 20 Cycles

4.5. SWAT Results

The mean time load percentage for decision support was 52.3% (SD 2.8), which was nearly identical to the mean time load percentage for automatic execution at 52.6% (SD 2.8) ($p = 1$). The mean mental effort percentage for automatic execution was 57.5% (SD 1.5) which approached being significantly higher ($p = 0.07$) than the decision support percentage 45.3% (SD 2.0) (Figure 15). The mean stress load percentage for automatic execution 33% (SD 2.2) was not significantly different ($p = 0.3$) than decision support 25% (SD 2.1).

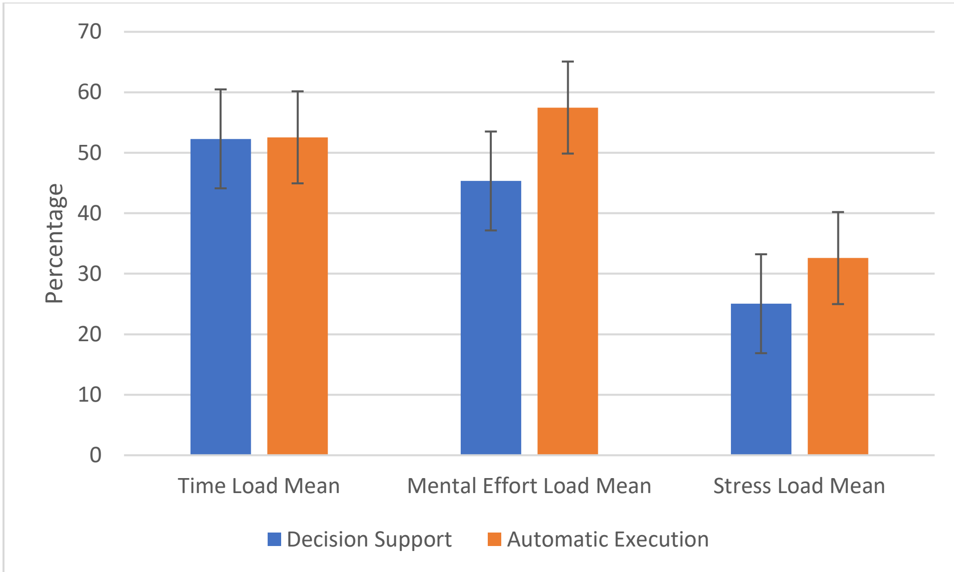

Figure 15. SWAT Results Means Comparison

5. Discussion

5.1. Review of the Research Objectives

The objective this research was to explore how collaboration with a robotic assistant affects cognitive workload when increasing automation from decision support to automatic execution. The experimental methods measured human cognitive workload and performance at a given level of automation compared to a control condition. The results illustrated a nearly significant increase in mental workload as automation increased and the participant became more immersed in the typing task and began operating out of the loop. Additionally, the results revealed a significant reduction in the time for the HRC team to complete 20 cycles as automation increased.

This experiment had high internal validity as it was conducted in a laboratory, limiting the influence of external variables such as multiple processes, operator experience, and separate requirements. The goal was to limit the potential for confounding factors. The external validity in this experiment is a weakness. The replication of results of the experiment may be difficult to achieve in an actual manufacturing environment due to the inevitable introduction of external variables which are controlled in a laboratory environment.

5.2. Interpretation of Results

Two hypotheses were identified prior to data collection. The first hypothesis, that the automatic execution human operator will be out of the loop while engrossed in the typing task and take more time to notice the error, understand the problem, correct the problem, then return the system to homeostasis than the decision support human operator was not supported by the results. The metrics of error intervention time and total cycle time can be used to test this hypothesis. While the means returned different values, statistically there was no significant difference in error intervention times during decision support or automatic execution when *t*-tests were performed comparing individual observation means or combined observation means of the treatments (Figure 12) (Figure 13). At the operational level, the total mean cycle time for automatic execution was significantly ($p < 0.0001$) shorter than the total mean cycle time for decision support (Figure14).

Two factors may partially explain these results. The first factor is trust. Trust is critical to establishing an operational HRC team. The human must develop trust that the robot will consistently deliver the intended outcome if they are going to allow themselves to shift cognitive workload away from an automated task (Endsley, 2017). This level of trust was not able to be established as the participants were given instruction on how to react if an error should occur, cueing them in that the automated system will not perform reliably during the experiment. When humans do not gain a satisfactory degree of trust in an automated system, the HRC team will not perform in concert with each other (Hancock et al., 2011). In this case, the participant perceived the risk of failure to outweigh the benefit of automation and did not trust the system to deliver desirable results consistently.

Thereby, participants accepted responsibility for both performance and outcomes of the system (Bradshaw et al., 2013).

The second set of factors are timing and communication. Given effective timing and communication, members of the HRC team can support each other's task interactions (Azhar & Sklar, 2017). Communication occurs when an HRC team member provides or requests information, then provide a response which furthers the process (Azhar & Sklar, 2017). Automatic execution had more uniform signaling prompts during its normal operation when compared to decision support affecting both timing and communication. During normal operations in automatic execution, signaling occurred when the object interrupted the light beam transmitted by the photoelectric switch. During normal operations in decision support signaling occurred when the human operator noticed that the object and robot where in the correct position to initiate the pick task. As a result of decision support operators' inability to match the signaling consistency of the automatic execution cycle there was variability in performance measurements. These deviations increased the total mean cycle time during decision support. While the individual error intervention times did not produce significant results when compared against the same observation in the alternate treatment, the accumulation of variation in signaling times combined over a period of 20 cycles produced a significant difference in the total cycle time where decision support took significantly longer to complete 20 cycles than automatic execution.

The second hypothesis, that the automatic execution operator will be more accurate in word processing and have lower subjective workload ratings than the decision support operator was not supported in the results of this experiment. The automatic execution EPM was not significantly higher ($p = 0.3$) than the decision support EPM. The data from the SWAT also did not support the hypothesis. The mental effort load mean approached significance ($p = 0.07$) measuring higher in automatic execution than in decision support. As the participant began operating out of the loop in automatic execution, they had to dedicate greater levels of mental workload to ensure that the operation was progressing harmoniously in a non-rhythmic manner when compared to decision support where the participant was engaged during each cycle.

This hypothesis was derived when considering cognitive workload management. Regulating cognitive workload factors has been observed to increase human performance (Gombolay et al., 2017). There is often a tradeoff of positive and negative cognitive effects with increased levels of automation. Automation levels that are either too high or low can have negative effects of the participants ability to accurately intervene or assume decision making authority (Gombolay et al., 2017). Cognitive workload levels have been reported to be lower when the human is acting as a collaborator rather than a supervisor (Azhar & Sklar, 2017). The human, in the decision support scenario, acted in more of a collaborative manner than in the automatic execution scenario and experienced nearly significant ($p = 0.07$) less overall cognitive effort ratings than the operator participating in automatic execution. While the time and stress load relationships have

been measured in previous studies, this study did not provide the adequate level of error complexity to produce large enough standard deviations in the participant's perceived time and stress loads to reveal significant differences in workload.

The findings from this study can be adapted and interpreted by management teams to improve the cognitive ergonomic conditions of their workers operating within HRC teams. During implementation, managers can design HRC relationships based on the degree of automation that may be appropriate for the human operator to maintain a desired level of cognitive workload capacity. For example, a hypothetical relationship may exist where error interventions may occur faster at increased levels of automation, but cognitive workload load ratings increase in the later stages of operation when compared to lower levels of automation.

Improved production outcomes for manufacturing organizations are also important applications of this study's findings. While significant differences were found in WPM and EPM when each treatment was compared to the control, no significant difference was found between the two treatments. The HRC team however completed 20 cycles significantly (p = 0.0001) slower during decision support than automatic execution indicating significant potential impacts on production values indicating the potential for increased performance.

5.3. Limitations

One of the major limitations to this experiment was the complexity of the error. Because the observation involved university students who were being recruited to perform a task that they were unfamiliar with, the level of complexity involved with the error could not be very high. As a result, the variability in the time it took participants to understand and correct errors was low. This resulted in means and standard deviations that were too similar to produce significant differences.

Another limitation in this study was observation time. The treatment observation lasted approximately 10 minutes. In an environment where the human may operate out of the loop as a member of a HRC team, the operation may cycle for hours before any interaction is needed from the human. In an environment where the HRC team executed a task for several hours, the human would likely experience cognitive fatigue and vigilance decrements resulting in reduced arousal to weak signaling. Having an observation that lasted for several hours was not practical though in a university laboratory setting.

5.4. Future Research

Based on the analysis of individual error interventions (Figure 12), assumptions can be made that in early phases HRC error intervention studies, participants are learning about their environment and their relationship to the automated system. As the participant becomes more engrossed in their task they begin to operate out of the loop. Humans operating out of the loop must regain situational awareness prior to understanding and

correcting an error occurring in an automated system (Endsley, 2017). Future researchers should explore a practical application of a technical error over a longer period. This would provide future researchers results with higher external validity and presumably more significant results due to more diverse error observation means and standard deviations which would result in more discrete *p*-values. Regression analysis could then be performed to identify trends in cognitive workload, performance over time.

Additionally, by using a measurement technique to quantify situational awareness such as the situational awareness global assessment technique (SAGAT) or the situational awareness rating technique (SART), future researchers can further explore the relationship between cognitive workload, performance, and situational awareness and how these factors are related to the automation conundrum. Production cost projections could be associated with the results to link cognitive ergonomic advantages to improved economic conditions for organizations with HRC teams.

6. Conclusion

The aim of this thesis was to determine how collaboration with a robotic assistant affects cognitive workload when increasing automation from decision support to automatic execution. To answer this question, the following two hypotheses were developed.

1. Automatic execution operators will be out of the loop while engrossed in the typing task and take more time to notice the error, understand the problem, correct the problem, and return the system to homeostasis than decision support operators.
2. Automatic execution operators will be faster and more accurate in word processing and have lower subjective workload ratings than decision support operators.

The first hypothesis was not supported by the results of the study. There was no significant difference in intervention time when the two treatments were compared, but the decision support HRC team took significantly more time to complete 20 cycles than the automatic execution HRC team. The second hypothesis was not supported by the results of this study. There was no significant difference in EPM when the treatments were compared. The automatic execution HRC team produced nearly significant increased cognitive effort results when compared to the decision support HRC team. These results were surprising based on the literature reviewed to support the research and the results of past research endeavors. What the results of the study revealed is that while increased automation may result in faster overall HRC performance, increased cognitive effort may be experienced by the human team member as the degree of automation increases.

The inspiration for the methods used to test these hypotheses was derived through the review of prior research initiatives. Particularly, research concerning cognitive workload management effects on human performance (Gombolay et al., 2017), HRC team interaction and task allocation (Azhar & Sklar, 2017), and the automation conundrum (Endsley, 2017) shaped the tasks and experiment design. The scope of the experiment was narrowed to automation levels 5 and 7 in Parasuraman's Levels of Automation of Decision and Action Selection (Parasuraman et al., 2000). As the human HRC team member moves from level 5 to level 7 they begin to shift responsibility from themselves to the automated system and have the potential to begin operating out of the loop. Unexpectedly, the experimental results did not support the hypotheses, however, they did reveal data that can be useful in industrial environments in terms of task allocation, manufacturing cycle times, and cognitive workload management. The methodology used in this experiment was limited by both observation time and complexity of the error. More profound results may be available to future researchers performing observations outside of a laboratory setting.

Based on the data collected and findings revealed in this study, practitioners should consider incorporating situational awareness measurement techniques to a similar study in an industrial environment that has incorporated the use of HRC teams. There, data can be collected over a longer period, with more complex error situations. Situational

awareness measurements can then be collected and analyzed to explore their relationship to cognitive workload and performance. Implications from this study would further enrich the understanding human relationships to robotic assistants.

HRC teams are becoming more commonplace in industrial environments. Understanding the aspects of automation management has direct implications on how practitioners address errors and interact with robotic assistants. Exploring the human out of the loop phenomena continues to fascinate researchers who seek to better understand the relationship between automation and cognitive workload. This experiment highlights a segment of the HRC relationship where the human begins to operate out of the loop. The findings are applicable to improving the cognitive ergonomic conditions of workers operating within HRC teams as well as their overall production outcomes. These results suggest that as automation increases, overall production time decreases. There is an inverse effect however on the human team member’s mental workload if they are performing a supervisory task. In this case, mental workload increases at higher levels of automation.

Appendix A. Subjective Workload Assessment Technique (SWAT).

Participant # _____

Trial # _____

Time Load, Mental Effort Load, and Stress Load Ratings

Often have spare time. Interruptions or overlap among activities occur infrequently or not at all.	Occasionally have spare time. Interruptions or overlap among activities occur frequently.	Almost never have spare time Interruptions or overlap among activities are very frequent, or occur all the time.
Very little conscious mental effort or concentration required. Activity is almost automatic, requiring little or no attention.	Moderate conscious mental effort or concentration required. Complexity of activity is moderately high due to uncertainty, unpredictability, or unfamiliarity. Considerable attention required.	Extensive mental effort and concentration are necessary. Very complex activity requiring total attention.
Little confusion, risk, frustration, or anxiety exists and can be easily accommodated.	Moderate stress due to confusion, frustration, or anxiety noticeably adds to workload. Significant compensation is required to maintain adequate performance.	High to very intense stress due to confusion, frustration, or anxiety. High to extreme determination and self-control required.

Appendix B. Informed Consent

Consent Form for a Non-Clinical Study

1. Study Title: How does collaboration with a robotic assistant affect cognitive workloads when increasing automation from decision support to automatic execution?

2. The purpose of this experiment is to measure the change in cognitive workload when increasing degrees of automation. We will accomplish this by collecting both quantitative and qualitative data through observations and questionaries. The study will take place over a period of 3 months. Your expected time in the study will be 25 minutes. You will first read this consent form and be given a verbal explanation of the experiment. If you agree to the terms of participation, you will sign the informed consent form. You will provide demographic information, as well as any limitations which may affect results. You will receive an orientation of the experiment, the Universal Robot and its role and their workstation. You will then be given three-minutes to make physical adjustments and practice typing the prologue. After a one-minute break, you will then provide a three-minute control sample of your typing ability. After a second one-minute break, if you are in Group One, you will participate in the decision support variant of the experiment. The Universal Robot has been programmed with a pick and place task. Execution of the pick task is signaled by a button placed on your workstation to the left of the keyboard. When an object is placed in the target area, you will press the button signaling the robot to pick up the object and place it in an adjacent bin. If you are in Group two, you will participate in the automatic execution variant of the experiment. The Universal Robot has been programmed with a pick and place task. The robot is signaled to execute the pick movement by an infrared sensor which is activated when an object is placed in the designated target area. You will supervise the operation of the robot while typing from the provided literature. The task will cycle twenty times. If at any time the object is placed outside the target area, intervene, and place the object back in the correct area to continue the production model.

3. Risks: You will be performing basic typing and pick and place activities while working with a collaborative robot. The total time allocated for the observation is approximately 25 minutes. Risks associated with working in proximity of robotic arms include impact and pinch points. Impact protection settings and power reduction while working in proximity of participants will be utilized. Your workstation will be separate from the robot. The examiner will supervise all activities closely. You will only be asked to approach the robot workstation when the robot is in a “wait” status and not moving. The Universal Robot is also programmed to perform emergency and safeguard protective stops if unintentional contact is detected. You may withdraw from the study at any time if you feel any sort of discomfort. Breaks will be provided between orientation, control testing, and the treatment. Breaks during data collection periods are not permitted though.

4. COVID-19 Mitigation: If you feel sick, please reschedule your trial. Face coverings will be used at all times in the lab. There is a hand sanitizing station provided at the entrance of the lab for your convenience. All workspaces, instruments, and equipment have been cleaned and sanitized prior to your arrival. For the safety of the investigator and the participant, 6ft social distancing will be observed while working in the lab.

5. Benefits: There are no direct benefits; however, this experiment may provide future information that is helpful in improving our understanding the assignment of degrees of automation to human/robot manufacturing teams. Other than the extra credit offered as compensation, participation or withdrawal from the experiment will have no impact on regular grading activates during the course. At the completion of the sessions, you will receive 0.5 points added to your final grade for your Industrial Engineering Course with your professor’s approval. Should you choose to withdraw, extra credit will not be awarded.

6. Alternatives (if applicable): Not Applicable.

7. Investigators: The following investigators are available for questions about this study, M-F, 8:00 a.m. - 4:30p.m. Laura Ikuma, PhD (likuma@lsu.edu), 225-578-5364, 3190R Patrick Taylor Hall, Mitchell Champagne (mcham41@lsu.edu), 504-881-3456, 2352 Patrick Taylor Hall

8. Performance Site: Louisiana State University and Agricultural and Mechanical College, 2352 Patrick Taylor Hall

9. Number of subjects: 46

10. Inclusion Criteria:

    - Individuals enrolled in any Industrial Engineering Course.
    - Above the age of 18.
    - Corrected or normal vision.
    - Have no cognitive disabilities that would affect the ability to perform a typing task or correct a placement error in a pick and place activity.
    - Have no pain that would affect the ability to perform a typing task or correct a placement error in a pick and place activity.

11. Exclusion Criteria: Individuals under age 18 or over age 65. If you have psychological or neurological conditions.

    - Individuals not enrolled in an Industrial Engineering Course.
    - Below the age of 18.
    - Uncorrected or abnormal vision in either eye
    - Cognitive disabilities that would affect the ability to perform a typing task or correct a placement error in a pick and place activity.
    - Current pain that would affect the ability to perform a typing task or correct a placement error in a pick and place activity.

12. Right to Refuse: At any time during the experiment, you have the right to not participate or withdraw from the study, however extra credit will not be awarded. You are expected to comply with the investigators’ instructions. If you fail to comply, you will be removed by an investigator from the experiment, and extra credit will not be awarded.

13. Privacy: The LSU Institutional Review Board (which oversees university research with human subjects) may inspect and/or copy the study records.

Results of the study may be published, but no names or identifying information will be included in the publication. Other than as set forth above, participant identity will remain confidential unless disclosure is legally compelled.

14. Signatures:
The study has been discussed with me and all my questions have been answered. I may direct additional questions regarding study specifics to the investigators. For injury or illness, call your physician, or the Student Health Center if you are an LSU student. If I have questions about subjects' rights or other concerns, I can contact Alex Cohen, Institutional Review Board, (225) 578-8692, irb@lsu.edu, or www.lsu.edu/research. I agree to participate in the study described above and acknowledge the investigator's obligation to provide me with a signed copy of this consent form.

Subject Signature:________________________________Date: ________________

For research involving the collection of identifiable private information one of the following <u>must</u> be listed on the consent form:

Identifiers might be removed from the identifiable private information. After removal, the information may be used for future research studies or distributed to another investigator for future research studies without additional informed consent.

Yes, I give permission____
Signature

No, I do not give permission____
Signature

Appendix C. IRB Approval

LSU | Office of Research & Economic Development

TO:	Laura H Ikuma LSUAM | Col of ENGR | MECH and IE - Industrial Engineering | CC00178
FROM:	Alex Cohen Chairman, Institutional Review Board
DATE:	14-Feb-2022
RE:	IRBAM-21-1422
TITLE:	EFFECT OF AUTOMATION LEVEL ON COGNITIVE WORKLOAD WHEN COLLABORATING WITH A ROBOTIC ASSISTANT
SUBMISSION TYPE:	Initial Application
Review Type:	Expedited Review
Risk Factor:	Minimal
Review Date:	14-Feb-2022
Status:	Approved
Approval Date:	14-Feb-2022
Approval Expiration Date:	13-Feb-2023
Expedited Categories:	07
Requesting Waiver of Informed Consent:	No
Re-review frequency:	Annually
Number of subjects approved:	46
LSU Proposal Number:	
By:	Alex Cohen, Chairman

Continuing approval is CONDITIONAL on:

1. Adherence to the approved protocol, familiarity with, and adherence to the ethical standards of the Belmont Report, and LSU's Assurance of Compliance with DHHS regulations for the protection of human subjects*
2. Prior approval of a change in protocol, including revision of the consent documents or an increase in the number of subjects over that approved.
3. Obtaining renewed approval (or submittal of a termination report), prior to the approval expiration date, upon request by the IRB office (irrespective of when the project actually begins); notification of project termination.
4. Retention of documentation of informed consent and study records for at least 3 years after the

study ends.

5. Continuing attention to the physical and psychological well-being and informed consent of the individual participants, including notification of new information that might affect consent.
6. A prompt report to the IRB of any adverse event affecting a participant potentially arising from the study.
7. Notification of the IRB of a serious compliance failure.
8. **SPECIAL NOTE: When emailing more than one recipient, make sure you use bcc. Approvals will automatically be closed by the IRB on the expiration date unless the PI requests a continuation.**

** All investigators and support staff have access to copies of the Belmont Report, LSU's Assurance with DHHS, DHHS (45 CFR 46) and FDA regulations governing use of human subjects, and other relevant documents in print in this office or on our World Wide Web site at http://www.lsu.edu/research*

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References

Admoni, H., Shah, J., & Srinivasa, S. (2017). Editorial: Special Issue on Human-Robot Interaction. *International Journal of Robotics Research, 36*(5-7), 459-460. doi:10.1177/0278364917712608

Antonelli, D., Astanin, S., & Bruno, G. (2016). Applicability of Human-Robot Collaboration to Small Batch Production. *Collaboration in a Hyperconnected World*, 24. Retrieved from http://libezp.lib.lsu.edu/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=edb&AN=119825615&site=eds-live&scope=site&profile=eds-main

Azhar, M. Q., & Sklar, E. I. (2017). A study measuring the impact of shared decision making in a human-robot team. *International Journal of Robotics Research, 36*(5-7), 461-482. doi:10.1177/0278364917710540

Bradshaw, J., Hoffman, R., Johnson, M., & Woods, D. (2013). The Seven Deadly Myths of “Autonomous Systems”. *Intelligent Systems, IEEE, May / June 2013*, 2-9. doi:10.1109/MIS.2013.70

Bureau of Labor Statistics. (2021, 03 November 2021). Economic News Release. *Employer-Reported Workplace Injuries and Illnesses (Annual) News Release.* Retrieved from https://www.bls.gov/news.release/archives/osh_11032021.htm

Chen, X., Bojko, M., Riedel, R., Apostolakis, K. C., Zarpalas, D., & Daras, P. (2018). Human-centred Adaptation and Task Distribution utilizing Levels of Automation. *IFAC PapersOnLine, 51*(11), 54-59. doi:10.1016/j.ifacol.2018.08.234

Endsley, M. R. (2017). From Here to Autonomy: Lessons Learned From Human–Automation Research. *Human Factors, 59*(1), 5-27. doi:10.1177/0018720816681350

Gombolay, M., Bair, A., Huang, C., & Shah, J. (2017). Computational design of mixed-initiative human–robot teaming that considers human factors: situational awareness, workload, and workflow preferences. *International Journal of Robotics Research, 36*(5-7), 597-617. doi:10.1177/0278364916688255

Gualtieri, L., Rauch, E., Vidoni, R., & Matt, D. T. (2019). An evaluation methodology for the conversion of manual assembly systems into human-robot collaborative workcells. *Procedia Manufacturing, 38*, 358-366. doi:10.1016/j.promfg.2020.01.046

Hancock, P., Billings, D., Schaefer, K., Chen, J. Y. C., de Visser, E. J., & Parasuraman, R. (2011). A Meta-Analysis of Factors Affecting Trust in Human-Robot Interaction. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 53*(5), 517-527. doi:10.1177/0018720811417254

Johnson, M., Bradshaw, J., Feltovich, P., Hoffman, R., Jonker, C., van Riemsdijk, B., & Sierhuis, M. (2011). Beyond Cooperative Robotics: The Central Role of Interdependence in Coactive Design. *IEEE Computer Society*, 81-88.

Johnson, M., Bradshaw, J., Feltovich, P., Jonker, C., van Riemsdijk, B., & Sierhuis, M. (2014). Coactive Design: Designing Support for Interdependence in Joint Activity. *Journal of Human-Robot Interaction, 3*(1), 43-69. doi:10.5898/JHRI.3.1.Johnson

Kildal, J., Martín, M., Ipiña, I., & Maurtua, I. (2019). Empowering assembly workers with cognitive disabilities by working with collaborative robots: a study to capture design requirements. *Procedia CIRP, 81*, 797-802. doi:10.1016/j.procir.2019.03.202

Kim, W., Lorenzini, M., Balatti, P., Wu, Y., & Ajoudani, A. (2019). Towards Ergonomic Control of Collaborative Effort in Multi-human Mobile-robot Teams. In (pp. 3005-3011): IEEE.

Luximon, A., & Goonetilleke, R. S. (2001). Simplified subjective workload assessment technique. *ERGONOMICS, 44*(3), 229-243. Retrieved from http://libezp.lib.lsu.edu/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=edswsc&AN=000166737300001&site=eds-live&scope=site&profile=eds-main

Makrini, I. E., Merckaert, K., Winter, J. D., Lefeber, D., & Vanderborght, B. (2019). Task allocation for improved ergonomics in Human-Robot Collaborative Assembly. *Interaction Studies, 20*(1), 102-133. doi:10.1075/is.18018.mak

Maurice, P., Padois, V., Measson, Y., & Bidaud, P. (2017). Human-oriented design of collaborative robots. *International Journal of Industrial Ergonomics, 57*, 88-102. doi:10.1016/j.ergon.2016.11.011

Parasuraman, R., Sheridan, T., & Wickens, C. (2000). A Model for Types and Levels of Human Interaction with Automation. *IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—, 30*(3), 286-297.

Pearce, M., Mutlu, B., Shah, J., & Radwin, R. (2018). Optimizing Makespan and Ergonomics in Integrating Collaborative Robots Into Manufacturing Processes. *IEEE Transactions on Automation Science & Engineering, 15*(4), 1772-1784. doi:10.1109/TASE.2018.2789820

Sadrfaridpour, B., Saeidi, H., & Wang, Y. (2016). An integrated framework for human-robot collaborative assembly in hybrid manufacturing cells. In (pp. 462-467): IEEE.

Universal Robots. (2022). Retrieved from https://www.universal-robots.com/

Weckenborg, C., & Spengler, T. S. (2019). Assembly Line Balancing with Collaborative Robots under consideration of Ergonomics: a cost-oriented approach. *IFAC PapersOnLine, 52*(13), 1860-1865. doi:10.1016/j.ifacol.2019.11.473

Wickens, C. D., Gordon, S. E., & Liu, Y. (1997). *An Introduction to Human Factors Engineering*: Addison-Wesley Longman Educational Publishers Inc. .

Vita

Mitchell Champagne was born in Slidell, Louisiana in 1984. He received his bachelor's degree in Agricultural Business from Louisiana State University in December 2008. In August 2018, he began his work toward a master's degree in Industrial Engineering at Louisiana State University. Mitchell has accrued 15 years of military experience as a U.S. Army officer and continues to serve in the Louisiana Army National Guard. Mitchell plans to earn his master's degree in August 2022.