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A Theoretical Framework For Evaluating Mental Workload Resources in Human Systems Design for Manufacturing Operations

A dissertation submitted in partial fulfilment
of the requirements for the degree of
Doctor of Philosophy

By

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2016
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WRIGHT STATE UNIVERSITY
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I HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER MY SUPERVISION BY Sharon Claxton Bommer ENTITLED A Theoretical Framework for Evaluating Mental Workload Resources in Human Systems Design for Manufacturing Operations BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Doctor of Philosophy in Engineering.

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Abstract

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Manufacturing is a human-driven process that applies energy and manpower to produce consumer goods. In repetitive task processes like manufacturing systems, optimal performance is extremely important for the production employee and the company. In the general fast pace of manufacturing operations, there is the potential for operator errors, which correlates to possible safety issues and loss of revenue. This research explores the influence of cognitive resources on operator performance in manufacturing operations using the Multiple Resource Theory (MRT) and mental workload measures. Computer simulation models and mathematical modeling with Improved Performance Research Integration Tool (IMPRINT) were used to assess mental workload resources to improve human system design for performance of the shop floor employee. This research presents the design, analysis and experimental implementation of a theoretical framework that provides a systematic approach for measuring mental workload using a combination of analytical and empirical techniques. Two experiments are presented to show the effectiveness of the proposed framework. As manufacturing operations become more complex, models can be used to provide recommendations for operator mental workload capacity planning. Therefore, this work is important to industry as manufacturing operations are changing by requiring more complex procedures, which increases the cognitive demand of the operator.

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I dedicate this work to the loving memory of my late parents, Mr. and Mrs. Charlie Claxton, Sr. They lived their lives demonstrating true examples of honesty, integrity and fortitude. Their unconditional love and spirit continue to resonate in my life.

1 INTRODUCTION

Manufacturing is a human-driven process that applies energy and manpower to produce goods. In repetitive tasks operations, like manufacturing systems, performance levels are extremely important for the operator and the company. The majority of efforts on human factors in manufacturing focuses on the physical ergonomic aspects. As manufacturing operations become more complex, and the nature of operations change, it is imperative to take a cognitive ergonomics approach as well. Lindblom & Thorvald (2014) attempt to address the question of how the understanding of cognitive load in manufacturing can lead to a better shopfloor workplace [1]. Unnecessary cognitive load was found to contribute to the Cognitive Work Environment Problems they present. The research presented here explores the influence of cognitive resources on operator performance in manufacturing operations using Multiple Resource Theory (MRT) and mental workload measures. Simulation and modeling with Improved Performance Research Integration Tool (IMPRINT) were used to assess mental workload (MWL) resources to improve human system design in a manufacturing environment.

The study of cognitive load in manufacturing operations is a new topic in cognitive ergonomics and the literature is limited relative to this type of cognitive assessment. Therefore, my research is important as it will advance the body of

knowledge relative to evaluating and mitigating cognitive load in repetitive task manufacturing operations.

The aim of this research is to explore the theory of cognitive ergonomics, in conjunction with mental workload applications to evaluate operator MWL resources in manufacturing operations, which require repetitive tasks, in efforts to improve operator performance and the human-system design. There are three objectives to achieve this goal:

1. To develop and test a framework to effectively examine MWL in manufacturing for repetitive task operations
2. To use IMPRINT MWL predictions, in order to assist with identifying any mental overload conditions
3. To design and implement a mitigation strategy for any overload conditions using MRT mapping for process modifications

Figure 1.1: Theoretical Framework

This research successfully developed and tested a framework (Figure 1.1), that provides a systematic approach to evaluating mental workload for repetitive

task processes. The framework iteratively evaluates and redesigns tasks to achieve effective human system design in this setting.

The basis of the proposed framework utilizes existing Human Factors methods for evaluating MWL. One of the fundamental contributions of this work is the integration of these methods for the purpose of evaluating and effectively designing tasks for the human in a manual operations setting. This work was approached in three phases (Figure 1.2): pilot, experiment #1 (computer simulation) and experiment #2 (assembly simulation).

Figure 1.2: Research Approach

Phase 1 (the pilot study) was an exploratory effort to determine the feasibility of the proposed framework. It consisted of a field study in the medical device domain. Phase 2 (experiment #1) used computer simulated scenarios of a supervisory control task in a laboratory experiment to test the framework; the Air Force Multi-Attribute Task Battery Software (MATB) software was the testbed. Lastly, phase 3 (experiment #2) used a repetitive assembly and inspection process to validate the framework. In this experiment, subjects worked with toy building blocks to simulate manual repetitive task processes by

manufacturing workers.

The primary research question asked whether the workload assessment portion of the proposed framework will coherently predict MWL for repetitive task processes in manufacturing. This hypothesis was tested by checking the correlation between different workload measures used within the framework for each task complexity level. In the supervisory control task (phase 2, experiment #1) two of the three mental workload measures were significantly correlated: the performance and physiological measures. Similarly, for the manual task (phase 3, experiment #2) the same two of the three mental workload measures were significantly correlated. In addition, in both experiments, the framework diagnosed: MWL differences for task complexity levels for each category of MWL measures, MWL differences between task complexity combinations and mental resource utilization to compare task complexity levels. These results were used to demonstrate that the framework accurately assesses MWL for repetitive task processes.

The secondary research question asked whether MWL affects performance in repetitive manufacturing operation tasks. In both experiments, measures of task performance were significantly correlated with physiological MWL measures. Therefore, it was found that increasing MWL generally leads to decreasing performance in repetitive task processes in a manufacturing context.

In summary, cognitive demands are becoming a predominate factor in manufacturing operations. This is because of the move towards more complexity in increasingly competitive manufacturing environments where there is a need to be more adaptive to production demands. The proposed framework provides a

systematic and innovative approach to incorporate cognitive factors in the design of assembly and inspection tasks. This work is relevant to the changing demands of the industry and can be applied across domains with repetitive task processes.

This dissertation is divided into eight chapters. Chapter 2 presents the research background in review of the theory relevant to creating the framework. In Chapters 3 and 4, the research objective and hypotheses are presented. Chapter 5 discusses the exploratory phase of the research, which was the pilot study. Chapters 6 and 7 discuss the experiments conducted to examine and validate the framework. Lastly, the theoretical contributions and applications of this work are laid out in chapter 8.

2 LITERATURE REVIEW

This section provides information from the bodies of knowledge on the topics of Mental Workload (MWL), MWL assessment techniques, the Multiple Resource Theory (MRT), Cognitive Ergonomics and the Improved Performance Research Integration Tool (IMPRINT). Each topic offers useful information for exploring mental workload application in manufacturing operations and supports the research objectives outlined in Chapter 3.

2.1 PRIOR RESEARCH MEASURING MENTAL WORKLOAD IN MANUFACTURING

Lindblom & Thorvald (2014) attempts to address the question of how the understanding of cognitive load in manufacturing can lead to a better workplace for shop floor workers[1]. In this study, a framework is proposed using the theory of nine Cognitive Work Environment Problems (CWEPs) to understand how task and work station designs influence an operator’s cognitive load. The types of CWEPs are disruption of thought, orientation and navigational problems, cognitive tunnel vision, strains on short-term memory, unnecessary cognitive strain/load, spatial “dizziness”, inconsistent information coding, problems with time-coordination of values, and problem identification of process status. The proposed framework is composed of three levels of factors that can affect mental

workload. Level 1 focuses on information processing, and the possible CWEPs that can influence the operator at this level are disruption of thought, strains on the short-term memory, unnecessary cognitive strain, and inconsistent information coding. This level focuses on the internal factors of the operator. Level 2 addresses the external factors that influences the creation of the working environment. At level 2 internal and external factors are coordinated to improve human performance. For instance, spatial layout and basic flow or workstations are considered. If tools and parts are used together, they should be placed together in the correct order. Lastly, level 3 addresses socially and culturally situated aspects of work, such as norms and work practices. This study presents relevant factors that can affect cognitive load in manufacturing. There was no empirical data to test or validate the framework; however, the work is still ongoing.

In another study, Thorvald & Lindblom (2014), presents the initial development of a cognitive load assessment tool for manufacturing operations[2]. The aim of this tool is to identify risk in tasks and workstation designs where a high cognitive load may lead to poor performance. The tool evaluates the task and workstation functions; it is made up of an evaluation form to assess a total of twelve factors that can influence the task or workstation. The task based factors are saturation, batch sizes, batching variance, level of difficulty, difficulty of tool use and level of attention required. On the other hand, the workstation based factors are number of tools used, mapping of assembly sequence to workstation design, parts identification, quality of instruction, information cost and poke-a-yoke and constraints. The combined score of the twelve factors gives an indication of cognitive effort that an operator may deploy. This study does

not include any validation method of the assessment tool.

Layer, Karwoski & Furr (2009) conducted an experiment to test the research question that human performance in manufacturing operations is contingent upon the operator's cognitive demands and perceived quality of work life attributes[3]. A field experiment was conducted at two manufacturing companies that performed fabrication and assembly processes. From this work, a model was developed for human performance (dependent variable), using two independent variables: cognitive demands and quality of work. Human performance was measured using production quality (number of quality problems) and schedule (% of completed task). The independent variable of cognitive demands was measured as an index of task complexity, worker adaptability, mental workload and goal motivations; these measures were obtained during a cognitive task analysis. Quality of work life was measured using a questionnaire to assess variables of supervision, empowerment, job satisfaction and learning considerations. The results of this work found human performance to be associated with the human cognitive load attributes involved with performing a task as well as the worker's perceived quality of work life elements. However, there was not a statistically significant correlation between cognitive demands and quality of work. This study used empirical data, cognitive task analysis and questionnaire data to model worker performance in a production system.

2.2 MENTAL WORKLOAD

With repetitive task operations, there is interaction between the operator and an assigned task; this is referred to as mental workload (MWL) or simply

‘workload’. This is an important measurement because it provides awareness as to where unacceptable performance may result from an increase in task demands. The demands on a task or grouping of tasks may include completing physical actions and/or executing cognitive tasks [4]. Mental workload describes the demands of tasks, that require the limited information processing capability of the brain, in much of the same way that physical workload characterizes the energy demand upon the muscles [5].

Mental workload can be broken into two parts: effective and ineffective. Effective workload (i.e. task load) is the minimum amount of workload produced by task requirements. This segment of the workload directly accomplishes the work [6]. On the other hand, ineffective workload could be avoided by workers because it does not directly contribute to completing a task [6]. Ineffective workload could be reduced by learning and training. Relative to execution strategies of tasks, effective workload correlates to fast and accurate actions, whereas ineffective workload is associated with error and inaccuracy. Effective workload needs the least attention because it relates to efficiency; however, “more attention is needed under the ineffective mode to control each stage of information processing” [6]. The assessment of mental workload is an important aspect in the design and evaluation of occupational tasks [7]. The interaction between an operator and an assigned task is an important measurement because it provides awareness as to where increased task demands could lead to a negative impact on human performance. Also, workload rises when the number or difficulty of tasks required to complete a goal increases, or when the times allocated for task completion decreases [8]. Regulating task demands, such that the operator is neither under-loaded nor overloaded, can increase safety, health,

comfort and long-range productivity [9], because high cognitive load for pro-longed periods can lead to inefficient processes, poor performance as well as ergonomic and mental health symptoms [1]. Therefore, mental workload has a direct effect on an operator’s ability to sustain or reach desired performance levels [6]. As cited (Jung & Jung, 2001), the concept of mental workload is associated with the difference between the amount of resources available by a person and the amount of resources needed for the task[10]. Hence, mental workload can be altered by changing the amount of resources available within the person or the demands required by the task on the operator. Workload measurements are used in various capacities to include system desirability and system optimization.

Mental workload is the dependent variable that will be measured in this study. There are three main methods for measuring MWL: subjective, physiological and performance related[11][12]. However, no method can perfectly measure MWL by itself [11], therefore, this study will utilize all three methods to increase the study’s diagnosticity of MWL.

2.3 SUBJECTIVE MEASURES

Subjective workload measures involve asking operators to offer their judgment on the cognitive effort required to complete a task after it has been performed [11][13]. This method is relatively non-intrusive, typically easy to implement and has gained significant theoretical support for its ability to provide sensitive measures of operator load [9]. According to Bommer and Fendley (2015), subjective measures have been widely used to assess mental workload, because these measurement tools have proven to be valid and

reliable[14]. Therefore, two subjective mental workload techniques will be applied in this research: National Aeronautics and Space Administration – Task Load Index (NASA-TLX) and the Workload Profile.

2.3.1 National Aeronautics And Space Administration – Task Load Index (NASA-TLX)

NASA-TLX is a subjective MWL assessment tool; it is the most commonly applied MWL assessment tool. It has been used in numerous domains including civil and military aviation, driving, nuclear, power plant control room operation and air traffic control and cited in previous studies, like [15][16][17]. Its utilization has extended far beyond its original application of aviation and crew complement. It is “being used as a benchmark against which the efficacies of other measures, theories or models are judged” [18]. It is taught in university courses and used in diverse situations such as aircraft certifications, operator rooms and nuclear power plant control rooms.

The NASA-TLX uses a multi-dimensional scale to measure operator task performance, which consists of six subscales:

1. Mental demand – measures whether the perceptual activity (e.g. thinking, looking, searching etc.) was easy or demanding
2. Physical demand – measures whether the physical activity (e.g. controlling, activating, etc.) was strenuous or relaxed
3. Temporal demand – measures how much pressure was felt with the pace of activity (e.g. slow, fast, hectic, etc.)
4. Effort – measures how difficult work was applied to accomplish the task

5. Performance – measures how satisfied the subject was with their execution of accomplish the tasks
6. Frustration level – measures how the subject felt during the task (e.g. irritated, relaxed, stressed, etc.)

There are seven steps to implementing the NASA-TLX, which are outlined in Figure 2.1. Step 1 of the process is to define the task subject to analysis. The next step requires conducting a Hierarchical Task Analysis (HTA) to clearly define and understand the steps of the task. (The HTA process is discussed at Section 2.9.) During step 3, participants are chosen to meet the needs of the experimental design. Once the participants are identified and chosen, they should be briefed (step 4) on the purpose of the study and the NASA-TLX method. In step 5, the task under analysis is performed. After the task is completed, the NASA-TLX rating procedure begins. This step includes completing a pair-wise comparison and completing the interval scale. The pair-wise comparison is a weighting procedure that presents 15 pairwise combinations to the participants and has them select the scale from each pair that has the most effect on the workload during the task under analysis [13]. The most common modification to the NASA-TLX has been to eliminate the weighting process all together [18]. This method has been referred to as the Raw NASA-TLX (RTLX); the sub-scale ratings are averaged to create an estimate of the overall workload. RTLX will be used in this research experiment as one of the subjective MWL validation tools. The interval scale (Appendix F) rates the six dimensions on a scale from 0 to 100, where 0 represents the lowest task demand and 100 is highest task demand with the exception of the performance dimension, 0 indicates high demand and 100 is low demand. The final action (step 7) is to calculate the overall workload score.

Figure 2.1: NASA-TLX Procedural Steps

2.3.2 Workload Profile

The Workload Profile is a multidimensional subjective workload assessment instrument that is based on the multiple resource model proposed by Wickens (1987) [13][19][9]. This assessment tool uses eight dimensions to collect data on the demands imposed by a task: perceptual/central processing, response selection execution, spatial processing, verbal processing, visual processing, auditory processing, manual output and speech output. This method provides an overall rating for each task as well as a rating for each of the workload dimensions. These multidimensional ratings should provide a good representation of MWL in order to categorize the manner in which the task is demanding [19].

Figure 2.2 outlines the nine steps of the Workload Profile Process as cited by Stanton et. al (2010). The first step of the process is to specify the tasks or scenario under analysis. Next, a HTA should be conducted in order to understand the task completely. Step 3 calls for a workload pro-forma to be created. The workload pro-forma (Appendix F) lists the tasks to be rated in random order down a column, and across the page the eight MRT workload dimensions are listed, which are stages of processing (perceptual/central vs. response), modalities of input (visual vs. auditory), output (manual vs. vocal), and codes of processing (verbal vs. spatial). The participants are chosen in step 4. In step 5, the participants are briefed on the purpose of the study. It is recommended that they receive a workshop on MWL, MWL assessment, MRT and the workload profile dimensions, in order to gain a clear understanding of the process; because, one disadvantage of this method is that participants have difficulty understanding the different dimensions, if there is limited experience of

psychology and human factors. Once participants have a clear understanding of the technique's process, in step 6, a pilot run with a small task should be performed to demonstrate how to complete the profile pro-forma. The task under analysis will be performed by the participants in step 7. Step 8 requires the completion of the workload profile pro-forma. During this step, participants rate the proportion of attentional resources used for each task. The participants assign ratings ranging from 0 to 1 for each of the MWL dimensions hypothesized in the Wicken's model. During the final step (step 9), the analyst computes the overall workload for each task by adding the ratings across the eight dimensions. The workload profile method will be the second subjective measure tool used in this research because it is based upon the sound underpinning theory of MRT, which is discussed further in Section 2.6

Figure 2.2: Workload Profile Procedural Steps

2.4 PHYSIOLOGICAL MEASURES

Physiological workload measures are applied largely to the continuous measurement of physical responses of the human body [12]. An advantage of these measures is they do not interfere with the primary-task performance, but depending upon the collection method there may be a degree of physical constraint imposed [5]. The use of this measurement technique as an indicator of MWL is based upon the assumption that as task demand increases, changes in various participant physical responses are noticeable [13]. These physical responses can be measured with various bodily activity: cardiac, brain, respiratory, speech measures, and eye. Eye activity will be used to evaluate performance during this test environment. These measures will be employed to support the subjective workload findings. As cited in Ahlstrom & Friedman-Berg (2005) [20], “findings indicate that blink rate, blink duration and saccade duration all decreased while pupil diameter, the number of saccades and the frequency of long fixations all increased with increased workload (Iqbal, Adamczyk, Zheng, & Bailey 2004, 2005; Iqbal, Zheng, & Bailey, 2004; Lin, Zhang, & Watson, 2003; Rognin, Grimaud, Hoffman, & Zeghal, 2004; Stein, 1992; Van Orden, 2000; Van Orden et al., 2000; Veltman & Gaillard, 1998; Zeghal, Grimaud, Hoffman, & Rognin, 2002)”. Two physiological measures will be used as the index to measure MWL in this experiment: fixations and pupil diameter. Fixations are moments when the eyes are relatively stationary. So, increased fixation duration can be interpreted as an indicator of increased mental workload. Just as, pupil diameter is an indication of cognitive effort; large pupil diameters indicate increased mental workload [21].

2.5 PERFORMANCE

When considering performance for repetitive motion operations, three factors were taken into account: the effect of unconscious cognition, the learning effect and calculated measures.

2.5.1 Unconscious Cognition

In repetitive task operations, there is the process of learning. Learning is a natural phenomenon, in which a worker's output improves as his productivity levels improve [22]. As an operator becomes more efficient in a process over-time and the learning reduces, an operator can experience unconscious cognition. Unconscious cognition is the "mental structure and process that, operating outside phenomenal awareness, nevertheless influences conscious experiences, thought and action" [23]. An example of unconscious cognition is the action required in driving an automobile. These actions, which are completed without apparent mental effort and regularly without the ability to remember what was done, are considered by some as being done unconsciously [24]. Unconscious cognition should have minimal effect on an operator's performance in manufacturing processes, similarly to driving a car in traffic, because regularly scheduled breaks, equipment breakdowns and quality interruptions are expected in repetitive motion operations, like assembly lines. During these breaks the phenomenon of forgetting takes place at various levels depending upon the length of the break. After each interruption, at the first cycle, learning starts over again which negates the concern of unconscious cognition. However, if one does experience unconscious cognition, according to Reinhard, Greifeneder and Scharmach (2013), unconscious processes are presumed to have far better processing capability than conscious thinking and as a result of this unconscious

Figure 2.3: The learning-forgetting process over time.

Figure Source: Jaber, Givi & Neumann, 2013 [27]

state, one should outperform conscious thought when decision-making problems are complex[25]. During this experiment, unconscious cognition will not be explored further due to the minimal impact in the context of this study.

2.5.2 Learning

“Learning refers to the improved operational efficiency and cost reduction obtained from repetition of tasks” [26]. Workers learn and improve work performance by repeating tasks over time. As workers learn, output levels improve, which decreases resource expenditure per unit and believably, improving product quality [22]. However, a worker’s performance can also regress as a result of forgetting and work interruptions (Figure 2.3).

Forgetting is an outcome of work interruptions, which becomes apparent by production rate reductions after an inoperative period and the manufacturability of lower quality products compared to production during continuous operation

[28]. Therefore, the ability to predict a worker's performance when work resumes improves production planning and resource allocation. In addition, incorporating learning into a production process decreases fatigue, which can also improve the performance of the system [27].

In order to model a worker's output, learning curves can be utilized. Learning curve analysis can be useful for predicting expected work rates in processes where output accountability is tracked [29]. In jobs with repetitive tasks, learning curves (LC) can mathematically depict a worker's performance [28]. According to Jaber (2011), this method is deemed as an efficient tool to monitor workers' performance in repetitive tasks, leading to reduced process loss due to the workers' inability in the first production cycles as reported by several studies (Argote, 1999; Dar-El, 2000; Salameh and Jaber, 2000; and Jaber et. al., 2008)[28]. LCs can be applied for the allocation of tasks to workers according to their learning profiles in order to control productive operations. Other applications of LCs include production planning, cost estimation and control, resource allocation, lot sizing and product pricing [22]. This theory applies to this research experiment because high performance with low mental effort is the most efficient combination of cognitive capacity, which can result from the theory of learning. The learning curve theory will not be applied in this theoretical framework; however, it is a factor that should be considered in future studies that can provide more extensive production data to measure performance.

2.5.3 Calculated Measures

According to Miller (2001) most performance measures have the ability to estimate fluctuations in high levels of workload[12]. As cited by Cegarra and

Chevalier (2008), studies have shown a correlation between poor performance in the main task and the mental workload experienced by participants[11]. The mental workload required in a given task can be assessed with performance metrics, such as time taken, speed, or number of errors [11]. Bubb (2005) defined human error probability (HEP) as the probability that a specific task under observation was accomplished defective during a certain timeframe[30]. This work will use the HEP calculation as a measure of error. Mathematically, HEP is expressed as follows:

$$\text{HEP} = \frac{\text{number of observed errors}}{\text{number of the possibilites for an error}}$$

Galy, Cariou and Melan (2012) cite a study by Fournier, Wilson and Swain (1999), in which evaluated subjects in a multi-tasking experiment and the results revealed that performance decreased as workload increased, implying that a decline in performance can be an indicator of MWL overload[31][32]. Therefore, the HEP metric should increase as MWL increases.

2.6 MULTIPLE RESOURCE THEORY

Multiple Resource Theory (MRT) is a predictive model that aids in understanding an operator's performance ability while multi-tasking in a complex environment [33]. A complex environment refers to a task that has a number of simultaneous activities which are time-shared [34]. When an individual performs a task, each operation deploys mental processing resources crucial to completing the task [35]. People are capable of multi-tasking until task demands exceed available resources. According to MRT, the human mind

can allocate several resources to task demands either individually or collectively to include: visual, auditory, cognitive, motor, and speech. When task demands overlap, fewer resources are available and MRT predicts that performance will degrade. When multiple task require competing resources, this could lead to a compromise in system safety and effectiveness. So, the primary value of the MRT model is predicting relative differences in multitasking among varying conditions[36].

MRT can predict performance breakdowns in high workload circumstances, such as tasks that require an operator to perform two or more activities at one time. This model can make practical predictions relative to performance breakdown regarding a human operator's ability to accomplish tasks like driving an automobile in traffic, a pilot landing an aircraft, or a secretary in a busy office [33]. The most significant application of MRT is its ability to recommend design or task changes when conditions of multitasking create resource overload [36]. Examples of strategies for reducing resource overload include automating parts of tasks, reassigning parts of a task to another operator, and changing task procedures such that process steps are performed sequentially instead of concurrent [5]. MRT uses four dimensions in the multiple resource model that justifies the variance in time-sharing of performance and each dimension has two discrete levels [33]. These dimensions are processing stages, perceptual modalities, visual channels and processing codes. Wickens (2008) defines the dimensions as follows[36]:

- Processing Stages: perceptual and cognitive tasks utilize different resources from the selection and execution of tasks

- Perceptual Modalities: auditory perception applies different resources than visual perception
- Visual Channels: differentiates between focal and ambient vision; focal vision supports object recognition, and ambient vision is responsible for perception of orientation and movement
- Processing Codes: spatial activity employs different resources than verbal/linguistic activity

MRT is important to this research because it provides a model to evaluate the various mental resources for different conditions in the manufacturing system.

2.7 COGNITIVE ERGONOMICS

Ergonomics, as cited [37], “promotes a holistic, human-centered approach to work systems design that considers the physical, cognitive, social, organizational, environmental and other relevant factors (Grandjean, 1986; Wilson and Corlett, 1995; Sanders and McCormic, 1993; Chapaniz, 1995, 1999; Salvendy, 1997; Karwowski, 2001; Vicente, 2004; Stanton et al., 2004)”. In addition, Coelho (2011) defines ergonomics as the scientific discipline involved with understanding the interactions with humans and other components of a system, and this profession applies theoretical principles, data and methods to design an optimized system for the well-being of the human and system performance[38]. There are three domains within the ergonomic discipline: physical, cognitive and organizational. This research will focus on the cognitive demands of an operator’s performance.

Cognitive ergonomics deals with the interaction between tools and the user, emphasizing the cognitive processes of understanding, reasoning, and the use of knowledge [39]. It is the ergonomics of mental processes to improve operator performance. Cognitive ergonomics is concerned with the psychological aspects of work, both in how work affects the mind and how the mind affects work [40]. This concept focuses on finding a balance between the human's cognitive abilities and limitations, as well as the machine, task and environment [41]. This can lead to a reduction in errors and better performance in the manufacturing domain. Cognitive ergonomics focuses on the quality of work, including the outcome, versus traditional or physical ergonomics looking at the quality of working [40]. Traditional ergonomics focused on reducing operator fatigue and discomforts in efforts to increase throughput. However, the nature of human work has changed dramatically from working with the body to working more with the mind as industrial systems have become more automated. The increased responsibility of technology along with the use of complex procedures have imposed more demand on operators [13]. Instead of physical endurance, sustained attention has become more important. Rather than physical strength, there is a greater need for problem solving skills. In place of physical dexterity, reasoning has become more significant. Also, physically demanding work that is performed simultaneously with a cognitive task can influence mental workload by weakening mental processing or decreasing performance[7]. Therefore, in order to improve human system design for performance in manufacturing, the system design should include cognitive ergonomics in order to evaluate the cognitive elements of a task.

Two ergonomic methods that can be used to evaluate the cognitive elements

in human system design are a Cognitive Work Analysis (CWA) and Applied Cognitive Task Analysis (ACTA). A CWA is a structured approach that systematically moves from analyzing mental demands to identifying visualizations and the decision-aiding concepts that will provide effective support to understanding the cognitive work [42]. The CWA approach can be used to describe the functional properties of the work domain under analysis, the nature of tasks that are conducted within the system, the roles of the different actors residing within the system, and the cognitive skills and strategies that they use to conduct activity within the system [13]. The CWA is composed of five different phases, which models different constraint sets: work domain analysis (WDA), control task analysis, strategies analysis, social organization and co-operation analysis (SOCA) and worker competencies analysis. The WDA phase models the system based on its purposes and the limitations enforced by the environment. A control task analysis is utilized to identify the tasks within the system and the constraints imposed on these tasks under various situations. The strategies analysis is used to see how different activities can be accomplished. In order to determine how social and technical factors can work in unison to enhance a system performance, the SOCA is used to identify how activity and its associated strategies can be distributed amongst human operators. The worker competencies analysis pinpoints the competencies that an ideal worker should display by addressing the strengths and weaknesses of the human operator in relation to the systems design.

The ACTA provides techniques, which can be used to analyze the mental demands required for a particular task. This methodology, compared to traditional task analysis, is most appropriate in exploring complex domains [43].

There are seven steps to the ACTA process (Figure 2.4), which are made up of four different methods: task diagram interview, knowledge audit interview, simulation interview and the cognitive demands table.

Figure 2.4: ACTA Process Steps

Step 1 is to select and define the task to be analyzed. Next, in step 2, the correct set of SMEs should be identified. During step 3, the task should be observed by the analyst in order to understand the participant roles all through the task. Step 4 is the task diagram interview, which provides the analyst with an in depth overview of the task that is being analyzed. During this process, the tasks that are highly challenging are highlighted. A diagram should be created to illustrate the task steps that require the most cognitive skills. In step 5, the knowledge audit interview draws attention to the tasks that require expertise. The subject matter expert (SME) is questioned for specific examples within the context of the task, critical cues and decision-making strategies. Next, the simulation interview (step 6) takes place while the task under analysis is being performed. The SME is probed on the cognitive processes relative to issues like situation awareness, and potential errors. Lastly (step 7), the cognitive demands table assimilates the data obtained from the task diagram, knowledge audit and

simulation interviews into one organized format.

In summary, collecting the appropriate information and presenting it in the right format is important to effectively analyze the cognitive requirements for a successful human system design. Therefore, the ACTA model will be utilized to understand the cognitive elements of the task in order to accurately apply the MRT rating scale in the Improved Performance Research Integration Tool (IMPRINT).

2.8 IMPROVED PERFORMANCE RESEARCH INTEGRATION TOOL

The Improved Performance Research Integration Tool (IMPRINT) is a human performance modeling approach, which is a computer-based discrete event simulation tool that can predict mental workload. It has analytical capabilities to include “human versus system function allocation, mission effectiveness modeling, maintenance manpower determination, mental workload estimation, prediction of human performance under extreme conditions and assessment of performance as a function of varying personnel skills and abilities” [44]. This tool was developed by the Human Research and Engineering Directorate (HRED) of the United States Army Research Laboratory (ARL). IMPRINT’s primary domain has been in the military sector [45][46][47][48]; however, this research will extend the use of the tool in the civilian manufacturing sector. IMPRINT models different scenarios allowing the human capability to be studied relative to MWL predictions, in order to develop an effective human-system design that uses the optimal range of mental resources. Discrete events, with their estimated task times, and MRT ratings, for

associated mental resources, are the simulation inputs. IMPRINT has a MWL element that defines workload relative to the MRT dimensions [36]. With this information (Figure 2.5), IMPRINT can formulate MWL predictions for varying task/design combinations.

Figure 2.5: IMPRINT Simulation Inputs and Output

IMPRINT does not provide guidance on how to mitigate mental overload to improve the system. So, the aim of this experiment is to assess various scenarios based upon the IMPRINT predictions in order to improve the human-system design. Based upon these predictions, the mental resource demands of these various scenarios will be mapped to the associated MRT ratings in IMPRINT for development of mitigation strategies.

2.9 HIERARCHICAL TASK ANALYSIS

The Hierarchical Task Analysis (HTA) provides inputs for the ACTA, Workload Profile, NASA-TLX and IMPRINT. It is a step-by-step methodology

to describing a task or system, and the task or system can be analyzed to any required level of detail. The HTA works by decomposing systems into a hierarchy of goals, sub-ordinate goals, operations and plans; it focuses on what the operator is required to do in terms of actions and/or cognitive processes to achieve a system goal [49]. The HTA specifies the overall goal of a particular system, the sub-goals to be undertaken to achieve this goal, the operations required to achieve each of the sub-goals specified and the plans, which are used to ensure that the goals are achieved [49]. It is a simplistic process that involves studying the task or system through observation, surveys, interviews, walkthroughs, and user trials to name a few. The data from these studies is then used to breakdown and describe the goals and sub-goals involved. The process of developing the HTA enables the analyst to deeply understand the task or system. The output of a HTA is extremely useful and forms the input for numerous human factors analyses, such as error analysis, interface design and evaluation and allocation of function analysis [13]. Therefore, an HTA will be used to understand and examine the manufacturing process in order to provide inputs for the workload model.

3 OBJECTIVES

The aim of this research is to explore the theory of cognitive ergonomics, in conjunction with mental workload applications to evaluate operator MWL resources in manufacturing operations, which require repetitive tasks, in efforts to improve operator performance and human-system design. There are three objectives to achieve this goal:

1. To develop and test a framework to effectively examine MWL in manufacturing for repetitive task operations
2. To use IMPRINT MWL predictions, in order to assist with identifying any mental overload conditions
3. To design and implement a mitigation strategy for any overload conditions using MRT mapping for process modifications

4 HYPOTHESIS

This work is composed of a primary and secondary hypothesis (Table 4.1). The primary hypothesis is that all of the MWL measures will indicate the same trend in results, showing a correlation amongst the measures for each task difficulty level. The aim of the primary hypothesis is to validate the proposed framework. The secondary hypothesis seeks to determine if there is a relationship between performance and MWL in manufacturing operations that require multitasking and repetitive tasks. Therefore, the secondary hypothesis is that there is a relationship between performance and MWL in manufacturing operations that require repetitive tasks and multitasking.

Table 4.1: Research Questions and Hypothesis

	Research Question	Associated Hypothesis
Primary	Will the inputs to the framework predict MWL resources for repetitive task processes in manufacturing?	H0: The framework will predict MWL for manufacturing operations. Therefore, the MWL measures used to test the framework will indicate the same trend in results, showing a significant correlation amongst the measures.
		H1: The framework will not predict MWL for manufacturing operations. Therefore, the MWL measures used to test the framework will not show a significant correlation amongst the measures.
Secondary	Does MWL affect performance in manufacturing operations that require repetitive tasks?	H0: There is a relationship between MWL and performance in repetitive manufacturing tasks.
		H1: There is not a relationship between MWL and performance in repetitive manufacturing tasks.

5 REDUCING MENTAL WORKLOAD RESOURCES IN HUMAN SYSTEMS DESIGN FOR MANUFACTURING OPERATIONS

5.1 ABSTRACT

Manufacturing is a human-driven process that applies energy and manpower to produce consumer goods. In repetitive motion operations like manufacturing systems, optimal performance is extremely important for the production employee and the company. In the general fast pace of manufacturing operations, there is the potential for operator errors, which correlates to possible safety issues and loss of revenue. This research explores the influence of cognitive resources on operator performance in manufacturing operations using Multiple Resource Theory and mental workload measures. Simulation and modeling with Improved Performance Research Integration Tool (IMPRINT) was used to assess mental workload resources to improve human system design for performance improvement of the shop floor employee. As manufacturing operations become more complex, these models can be used to provide recommendations for operator mental workload reduction.

5.2 INTRODUCTION

Manufacturing is a human-driven transformation process that applies energy and manpower to produce consumer products of economic value [50]. Therefore, in repetitive motion operations like manufacturing systems, optimal performance is extremely important for the production employee and the company. Performance optimization influences safety in the environment and profitability. In the general fast pace of manufacturing operations, there is the potential for operator errors, which correlates to possible safety issues and loss of revenue. Therefore, the area of manufacturing is moving away from forced-focused activity to cognitive control activity. Cognitive control activity applies cognitive ergonomics, which studies processes during work with a concentration in understanding a situation to support reliable, effective and satisfactory performance [51]. It evaluates problems relative to attention distribution, decision making, the formation of learning skills, usability of human-computer systems, cognitive aspects of mental load, stress and human errors at work [51]. The aim of this research is to explore the theory of cognitive ergonomics, in conjunction with mental workload (MWL) applications to reduce operator MWL resources in manufacturing operations that require repetitive motions in efforts to improve operator performance and human-system design in manufacturing. This is important because MWL can have an immediate impact on operator performance by causing slower task performance and errors. As cited by Xie and Salvendy [6], optimizing the allocation of operator mental workload could reduce human errors, improve system safety, increase productivity and increase operator satisfaction. This paper proposes a general framework to analyze mental workload in manufacturing operations for

repetitive motion tasks. The framework models the mental resources associated with workload during task performance. A pilot study is performed to test the model.

5.3 BACKGROUND

5.3.1 Mental Workload

The assessment of mental workload is an important aspect in the design and evaluation of occupational tasks [7]. The interaction between an operator and an assigned task is an important measurement because it provides awareness as to where increased task demands could lead to a negative impact on human performance. Regulating task demands, such that the operator is neither under-loaded nor overloaded, can increase safety, health, comfort and long-range productivity [9]. Therefore, mental workload has a direct effect on an operator's ability to sustain or reach desired performance levels [6]. As cited by Jung and Jung [10], the concept of mental workload is associated with the difference between the amount of resources available by a person and the amount of resources needed for the task. Hence, mental workload can be altered by changing the amount of resources available within the person or the demands required by the task on the operator. This experiment utilizes the Multiple Resource Theory (MRT) to understand the demands required by the task on the operator.

5.3.2 Multiple Resource Theory

Multiple Resource Theory (MRT) is a predictive model that aids in understanding an operator's performance ability while multi-tasking in a

complex environment [33]. A complex environment refers to a task that has a number of simultaneous activities which are time-shared[34]. People are capable of multi-tasking until task demands exceed available resources. According to MRT, the human mind can allocate several resources to task demands either individually or collectively to include: visual, auditory, cognitive, motor, and speech. When task demands overlap, fewer resources are available and MRT predicts that performance will degrade when multiple task require competing resources, which could lead to a compromise in system safety and effectiveness. So, the primary value of the MRT model is predicting relative differences in multitasking among varying conditions [36]. MRT can predict performance breakdowns in high workload circumstances, such as tasks that require an operator to perform two or more activities at one time. This model can make practical predictions relative to performance breakdown regarding a human operator’s ability to accomplish tasks like driving an automobile in heavy traffic, a pilot landing an aircraft, or a secretary in a busy office [33]. The most significant application of MRT is its ability to recommend design changes when conditions of multitasking create resource overload [36]. MRT is important to this research because it provides a model to evaluate the various mental resources for different conditions in the manufacturing system.

5.3.3 Cognitive Ergonomics

Ergonomics, as cited by Karwowski [37], “promotes a holistic, human-centered approach to work systems design that considers the physical, cognitive, social, organizational, environmental and other relevant factors”. In addition, Coelho[38] defines ergonomics as the scientific discipline involved with understanding the interactions with humans and other components of a system,

and this profession applies theoretical principles, data and methods to design an optimized system for the well-being of the human and system performance. There are three domains within the ergonomic discipline: physical, cognitive and organizational. This research will focus on the cognitive demands of an operator's performance. Cognitive Ergonomics is the ergonomics of mental processes to improve operator performance. This concept focuses on finding a balance between the human's cognitive abilities and limitations, as well as the machine, task and environment[41]. This can lead to a reduction in errors and better performance in the manufacturing domain. Cognitive ergonomics focuses on the quality of work, including the outcome, versus traditional or physical ergonomics looking at the quality of working [40]. Traditional ergonomics focused on reducing operator fatigue and discomforts in efforts to increase throughput. However, the nature of human work has changed dramatically from working with the body to working more with the mind as industrial systems have become more automated. Instead of physical endurance, sustained attention has become more important. Rather than physical strength, there is a greater need for problem solving skills. In place of physical dexterity, reasoning has become more significant. Also, physically demanding work that is performed simultaneously with a cognitive task can influence mental workload by weakening mental processing or decreasing performance [7]. Therefore, in order to improve human system design for performance in manufacturing, the system design should include cognitive ergonomics in order to evaluate the cognitive elements of a task. This research uses an Applied Cognitive Task Analysis (ACTA) model to examine the cognitive elements of the task under evaluation.

5.3.4 Applied Cognitive Task Analysis

An Applied Cognitive Task Analysis (ACTA) can be used to evaluate the cognition elements in human system design. The ACTA provides techniques, which can be used to analyze the mental demands required for a particular task. This methodology, compared to traditional task analysis, is most appropriate in exploring complex domains [43]. The ACTA is made up of four methods: task diagram interview, knowledge audit interview, simulation interview and the cognitive demands table. These ACTA techniques were established to develop techniques that would enable system designers to draw critical cognitive elements from Subject Matter Experts (SMEs) [52]. ACTA has been applied in various domains as cited [53][43][54]. There are seven steps to the ACTA process (Figure 5.1):

Figure 5.1: Applied Cognitive Task Analysis Process Steps

Step one defines the task that will be analyzed. Next, the necessary participants or SMEs for the study should be identified. The third step involves observing the task to understand the role of the participants. Step four is to perform a task diagram interview. The task diagram interview provides the

analyst with an in depth overview of the task that is being analyzed. During this process, the tasks that are highly challenging are highlighted. A diagram should be created to illustrate the task steps that require the most cognitive skills. Next, in step five, the knowledge audit interview is conducted. The knowledge audit interview draws attention to the tasks that require expertise. The SME is questioned for specific examples within the context of the task, critical cues and decision-making strategies. The simulation interview is carried out in step six. The simulation interview takes place while the task under analysis is being performed. The SME is probed on the cognitive processes relative to issues like situation awareness, and potential errors. The final step is step eight, which is to build the cognitive demand table. The cognitive demands table assimilates the data obtained from the task diagram, knowledge audit and simulation interviews into one organized format. The ACTA model is utilized to understand the cognitive elements of the task in order to accurately apply MRT.

5.3.5 Improved Performance Research Tool (IMPRINT)

The Improved Performance Research Integration Tool (IMPRINT) is a human performance modeling approach, which is a computer-based discrete event simulation tool that can predict mental workload. It has analytical capabilities to include “human versus system function allocation, mission effectiveness modeling, maintenance manpower determination, mental workload estimation, prediction of human performance under extreme conditions and assessment of performance as a function of varying personnel skills and abilities” [44]. This tool was developed by the Human Research and Engineering Directorate (HRED) of the United States Army Research Laboratory (ARL). IMPRINT’s primary domain has been in the military sector[35][46][47][48];

however, this research will extend the use of the tool in the civilian manufacturing sector.

IMPRINT models different scenarios allowing the human capability to be studied relative to MWL predictions, in order to develop an effective human-system design that uses the optimal range of mental resources. Discrete events, with their estimated task times, and MRT ratings, for associated mental resources, are the simulation inputs. With this information, IMPRINT can formulate MWL predictions for varying task/design combinations. IMPRINT does not provide guidance on how to mitigate mental overload to improve the system. So, the aim of this experiment is to model various scenarios based upon the IMPRINT predictions in order to improve the human-system design. Based upon these predictions, studies will be ran to mitigate any overload conditions and map the mental resources back to MRT.

5.4 OBJECTIVES

The goal of this research is to explore the theory of cognitive ergonomics, in conjunction with mental workload applications to reduce operator MWL resources in manufacturing operations, which require repetitive motions, in efforts to improve operator performance and human-system design in manufacturing. There are three objectives to achieve this goal. The first objective is to develop and test a framework to effectively examine MWL in manufacturing for repetitive motion operations. The second objective is to use IMPRINT MWL predictions, in order to assist with identifying any mental overload conditions. The third objective is to mitigate any overload conditions using MRT mapping for process modifications.

5.5 METHODOLOGY

A framework was applied in the medical device domain for the production of a medical surgical implant for humans. After the parts are laser welded, they go through post processing to clean and check the quality specifications of the devices. This is a repetitive process, such that the same procedure must be followed every cycle. For this study, a segment of the process was analyzed: part cleaning. Process steps for parts cleaning include mixing acids for proper formulation, dipping parts in chemicals and monitoring equipment settings to track proper processing times. To study the manufacturing system, experienced real-world process operators that regularly perform the part cleaning process were used in on-site interviews and process walkthroughs for data collection to test the framework.

There are five primary steps to the framework: study the manufacturing system, apply MRT, predict MWL, reduce task overload and revise job variation. In step 1, the manufacturing operation is studied to gain knowledge and insight of the system. A Hierarchical Task Analysis (HTA) is performed to understand the task activity under analysis. Next, an Applied Cognitive Task Analysis (ACTA) is used to evaluate the cognition elements in the human system design (Appendix B). The HTA and ACTA collectively define the process steps and cognitive elements, which are used as discrete events in IMPRINT. During step 2, MRT is applied using the scale in IMPRINT to assess the mental resources utilized in completion of the process task's discrete events. This step provides MRT ratings for each discrete event identified in step 1; these ratings are inputs for IMPRINT. In the next step, mental workload is measured by simulating the process in IMPRINT. The discrete

events, with their estimated task times, and MRT ratings, for associated mental resources, are the simulation inputs. With this data (Figure 5.2), IMPRINT outputs the workload predictions and provides a workload profile for the defined task.

Figure 5.2: IMPRINT Simulation Inputs and Output

If there is a MWL overload, an analysis using MRT will be done to determine the attribution of mental resources that correlate to the mental overload. (If a mental overload condition is not measured this will end the process.) In the event of a mental overload situation, the manufacturing system is modified based on the MRT principles to reduce the resources contributing to the mental overload, and the MRT is applied again to compare the modified system resources to the baseline. And, once again, the MWL is measured using IMPRINT. This loop will continue until an optimal solution range is determined. Once an optimal range is achieved, a different variations of job sequencing is tested on the shop floor. The different job variations and its associated load will be documented to create a cognitive ergonomic index for quick reference.

The following flowchart (Figure 5.3 illustrates the research framework and approach for this study:

Figure 5.3: Research Framework

5.6 RESULTS

The mental resource values of for this study were mapped using the MRT rating scale as defined in IMPRINT. Figure 5.4 shows the resource usage for this process. The pie chart illustrates that the fine motor and visual demands are both higher than cognitive demands for this task. Only 1% of the task demands are associated with auditory cues and 2% with gross motor demands.

Figure 5.4: MRT Mapping

The workload profile output from IMPRINT is as follows:

proposed methodology, because there is not an overload to mitigate. However, to evaluate this process further, we chose to simulate it under time compression by combining cleaning inspection tasks. The process was simulated with two different conditions: three tasks overlapped with a reduction of 8 seconds in the overall process and two tasks overlapped with a reduction of 4 seconds in the overall process. The load was manipulated at 2 minutes and 2 seconds into the simulation. Given the task overlap and time reduction, IMPRINT predicts the following workload profiles (Figures 5.6 and 5.7):

Figure 5.6: Two-Task Overlap Workload Profile

The workload profile of the compressed process indicates that combining two of the inspection tasks (Figure 5.6) will not create a mental overload for the operator; IMPRINT predicts a workload value of 40. However, when three inspection tasks were overlapped (Figure 5.7), an overload was predicted at 2 minutes and 2 seconds in the simulation with a value of 120, which could potentially cause process errors or safety issues.

Figure 5.7: Three-Task Overlap Workload Profile

5.7 CONCLUSION

In this paper, a methodology to evaluate mental workload in manufacturing operations was presented. A pilot test was conducted in the medical device domain to test the framework. The results predict that overlapping more than two inspection tasks during the cleaning process would be unmanageable by the operator, because three task overlap experienced a workload value of 120, which exceeded the threshold value of 60. Meaning any workload value over or near 60 could potentially provide the operator a state of high load, which possibly cannot be performed effectively [8][45]. The findings demonstrate that the proposed framework could be used during design and set-up stages of a process to construct better operations in efforts to reduce mental overload for the operator in repetitive motion tasks. When looking at the results of this pilot study, this model can be valuable for understanding operator MWL resources in human-machine design for capacity planning of process set-up for a system that

is not built and modifications for an existing system to improve the design of modern manufacturing processes that require more cognitive demands. This work can be expanded by adding performance measures and workload assessments to the proposed framework for further validation. Subjective workload assessment techniques and psychological measures can be used to validate the simulation results. As cited by Bommer and Fendley [14], subjective measures, which are based upon the judgment of the operator, have been widely used to assess mental workload, because these measurement tools have proven to be valid and reliable. In order to gather the physiological data to support the workload subjective measures, eye tracking will be utilized in further studies. Also, more studies will need to be conducted to validate the appropriate MWL threshold by analyzing where increased task demands degrade performance.

5.8 ACKNOWLEDGEMENT

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6 A THEORETICAL FRAMEWORK FOR EVALUATING MENTAL WORKLOAD RESOURCES IN HUMAN SYSTEMS DESIGN FOR MANUFACTURING OPERATIONS

6.1 ABSTRACT

As the nature of manufacturing work is changing, requiring more cognitive demands, there is a need to develop system models for measuring and predicting human performance in repetitive task operations. This paper presents a theoretical framework, which provides a systematic approach for measuring mental workload using a combination of analytical and empirical techniques: human performance modeling with a computer simulation and mathematical modeling, along with physiological, subjective and performance measures. For this study, the Air Force Multi-Attribute Task Battery Software (MATB) software was used to model multitasking in a controlled environment to validate the theoretical framework. The independent variable of task complexity was measured, in the modeling of resource demands for a cleaning-inspection process and a final inspection process, using three dependent variables (subjective, physiological and performance measures) with a total of four responses (NASA-TLX, Workload Profile, fixation duration and human error probability).

The results indicate no significant difference among the response variables for each task complexity level, indicating the model accurately represents the operator's workload. Additional analysis shows accurate predication from the model in analyzing workload peaks.

6.2 INTRODUCTION

Manufacturing is a human-driven transformation process that applies energy and manpower to produce consumer products of economic value [50]. In repetitive task operations like manufacturing systems, performance optimization influences safety in the environment and profitability. In the general fast pace of manufacturing operations, there is the potential for operator errors, which correlates to possible safety issues and loss of revenue. For example, an assembly worker performing a manual assembly task is constantly exposed to situations with varying mental demands. Aspects of these demands to consider are the amount of information, time pressure, interruptions, rapid decisions, component batch sizes and the work station physical layout [1]. A high workload task that can encompass each of these aspects is that of inspection. The traditional role of quality inspectors is changing from dedicated quality inspectors to operators who perform multiple duties while attempting to perform inspection tasks [55]. This transforms the task from a sequential task to one of multitasking. Multitasking is becoming more prevalent in manufacturing operations.

There is a large body of literature on physical ergonomics for process improvements, but limited studies on cognitive ergonomics relative to mental workload (MWL) in manufacturing. Cognitive ergonomics focuses on the quality of work, including the outcome, versus traditional or physical ergonomics

looking at the quality of working [40]. Traditional ergonomics focused on reducing operator fatigue and discomforts in efforts to increase throughput. However, the nature of human work has changed dramatically from working with the body to working more with the mind as industrial systems have become more automated. Also, the increased responsibility of technology along with the use of complex procedures have imposed more demand on operators [13]. Instead of physical endurance and strength, sustained attention and problem solving skills have become more important. Also, physically demanding work that is performed simultaneously with a cognitive task can influence mental workload by weakening mental processing or decreasing performance [7]. Therefore, in order to improve human systems design for performance in manufacturing, the system design should include cognitive ergonomics in order to evaluate the cognitive elements of a task. As a result, the aim of this research is to explore the theory of cognitive ergonomics in manufacturing operations that require repetitive tasks. A theoretical framework, using a combination of analytical and empirical techniques, is proposed to improve operator performance and human-system design through the use of mental workload applications to adjust operator mental workload utilization. This study uses the Air Force MATB (Section 6.4.8) simulated environment to test the theoretical framework. MATB is a program of general piloting tasks that was originally developed by NASA to evaluate human performance for multi-tasking scenarios. The structure of this paper is as follows: Section 6.3 discusses theory relative to creating the theoretical framework. Section 6.4 reviews the experimental framework and methodology. Section 6.5 presents the research findings. Lastly, section 6.6 presents the conclusion and discussion.

6.3 THEORY

The following concepts of Cognitive Ergonomics, Mental Workload (MWL) and the Multiple Resource Theory (MRT) offer useful information for exploring mental workload applications in manufacturing operations. Each of these topics are inputs into the theoretical framework presented here.

6.3.1 Cognitive Ergonomics

Cognitive ergonomics studies processes during work with a concentration in understanding a situation to support reliable, effective and satisfactory performance [51]. It evaluates problems relative to attention distribution, decision making, formation of learning skills, usability of human-computer systems, cognitive aspects of mental load, stress and human errors at work [51]. Numerically controlled machines, group technology, cellular manufacturing and Just-In-Time production systems have revolutionized the manner in which products are designed and manufactured; these advances have transformed the role of the human operator in the manufacturing environment [55]. Cognitive ergonomics deals with the interaction between tools and the user, emphasizing the cognitive processes of understanding, reasoning, and the use of knowledge [39]. It is the ergonomics of mental processes to improve operator performance by understanding how work affects the mind and how the mind affects work [40]. This concept focuses on finding a balance between the human's cognitive abilities and limitations, as well as the machine, task and environment [41]. This can lead to a reduction in errors and better performance in the manufacturing domain. The application of cognitive ergonomics in manufacturing operations is important because the nature of human work in manufacturing has changed considerably from working with the body to working more with the mind with

the implementation of more automation and complex process procedures.

6.3.2 Mental Workload

With repetitive task operations, there is interaction between the operator and an assigned task; this is referred to as mental workload (MWL) or simply ‘workload’. This is an important measurement because it provides awareness as to where unacceptable performance may result from an increase in task demands. The demands on a task or grouping of tasks may include completing physical actions and/or executing cognitive tasks [4]. Mental workload describes the demands of tasks, that require the limited information processing capability of the brain, in much of the same way that physical workload characterizes the energy demand upon the muscles [5]. The assessment of mental workload is an important aspect in the design and evaluation of occupational tasks [7]. The interaction between an operator and an assigned task is an important measurement because it provides awareness as to where increased task demands could lead to a negative impact on human performance. Also, workload rises when the number or difficulty of tasks required to complete a goal increases, or when the times allocated for task completion decreases [8]. Regulating task demands, such that the operator is neither under-loaded nor overloaded, can increase safety, health, comfort and long-range productivity [9], because high cognitive load for pro-longed periods can lead to inefficient processes, poor performance as well as ergonomic and mental health symptoms [1]. Therefore, mental workload has a direct effect on an operator’s ability to sustain or reach desired performance levels [6]. As cited by Jung & Jung (2001), the concept of MWL is associated with the difference between the amount of resources available to a person and the amount of resources needed for the task[10]. At the point

when task demands exceed operator capacity, high levels of MWL occur [56]. The workload can be modified by adjusting available resources within the person, or the required task demands on the operator. The next section discusses the application of the Multiple Resource Theory to predict mental resources and demand usage while performing tasks.

6.3.3 Multiple Resource Theory (MRT)

Multiple Resource Theory provides a predictive model to better understand the relationship between resources and demands while multi-tasking in a complex environment [33]. When an individual performs a task, they expend mental operations, and to some extent, each operation deploys mental processing resources crucial to completing the task [35]. People are capable of multi-tasking until task demands exceed available resources. In order to provide safe and efficient operations of complex systems, the mental workload required by the users should not exceed their capacity [57]. According to MRT, the human mind can allocate several resources to task demands either individually or collectively to include: visual, auditory, cognitive, motor, and speech. When task demands overlap, fewer resources are available and MRT predicts that performance will degrade when multiple tasks require competing resources. This could lead to a compromise in system safety and effectiveness.

MRT can predict performance breakdowns in high workload circumstances, such as tasks that require an operator to perform two or more activities at one time. This model can make practical predictions relative to performance breakdown regarding a human operator's ability to accomplish tasks [33]. A significant application of MRT, and one employed in this study, is its ability to recommend design or task changes when conditions of multitasking create

resource overload [36]. Examples of reducing resource overload may include automating parts of tasks, reassigning parts of a task to another operator, or changing task procedures such that process steps are performed sequentially instead of concurrently [5]. MRT uses four dimensions in the multiple resource model that justifies the variance in time-sharing of performance, and each dimension has two discrete levels [33]. These dimensions are processing stages, perceptual modalities, visual channels and processing codes. Wickens (2008) defines the dimensions as follows[36]:

1. Processing Stages: perceptual and cognitive tasks utilize different resources from the selection and execution of tasks,
2. Perceptual Modalities: auditory perception applies different resources than visual perception,
3. Visual Channels: differentiates between focal and ambient vision; focal vision supports object recognition, and ambient vision is responsible for perception of orientation and movement,
4. Processing Codes: spatial activity employs different resources than verbal/linguistic activity.

MRT is applied to this research by providing a model to evaluate the various mental resources for different conditions in the manufacturing system.

6.4 METHODOLOGY

6.4.1 Theoretical Framework

The theoretical framework is made up of six primary steps (Figure 6.1). In step 1, the manufacturing operation is studied to gain knowledge and insight of the system. Tools used for this assessment are an Applied Cognitive Task Analysis (ACTA) and Hierarchical Task Analysis (HTA). Next, Multiple Resource Theory (MRT) is applied in step 2 to assess the mental resources utilized to complete the process tasks. Simulation modeling (IMPRINT) is deployed in Step 3. Step 4 measures mental workload using subjective, performance and physiological measures. During step 5, the data from Steps 3 and 4 is analyzed to determine the MWL condition (i.e. overloaded or under-loaded). If there is a MWL overload, an analysis using MRT will be done to determine the attribution of mental resources that correlate to the mental overload and/or performance errors. (If a mental overload condition is not measured, the process can end.) In the event of a mental overload situation, the manufacturing system can be modified (step 6) based on the MRT principles to reduce the resources contributing to the mental overload, and the MRT will be applied again to compare the modified system resources to the baseline. Likewise, for capacity planning, if an under-loaded condition exists, the process can be modified and mapped back to MRT. Once again, the MWL is measured. This loop continues until an optimal workload range is obtained. Mitchell (2000) defines “optimal” workload as “a situation in which the operator feels comfortable, can manage task demands intelligently, and maintain good performance (Hart, 1991, p.3)”[58].

Figure 6.1: Theoretical Framework for Evaluating MWL

6.4.2 MWL Inputs

Mental workload is the dependent variable that is measured in this study. There are three main methods for measuring MWL: subjective, physiological and performance related[11][12][31]. However, no method can perfectly measure MWL by itself [11], therefore, this study utilizes all three methods to increase the theoretical framework’s diagnosticity of MWL.

6.4.3 Subjective Workload Measures

Subjective workload measures are mostly question-answer type responses to varying levels of workload. These measures involve asking participants to offer their judgment on the cognitive effort required to complete a task after it has been performed [11][13]. This method is relatively non-intrusive, typically easy to implement and has gained significant theoretical support for its ability to provide sensitive measures of operator load [9]. As cited by Bommer and Fendley (2015), subjective measures, which are based upon the judgment of the operator, have been widely used to assess mental workload, because these measurement tools have proven to be valid and reliable[14]. In the Bommer and

Fendley (2015) study, two subjective measures were used to measure MWL and both scales showed the same trend for MWL assessment[14]. Similarly, two subjective mental workload techniques will be applied in this research: National Aeronautics and Space Administration – Task Load Index (NASA-TLX) and the Workload Profile.

National Aeronautics And Space Administration – Task Load Index

NASA-TLX is a subjective MWL assessment tool; it is the most commonly applied MWL assessment tool. It has been used in numerous domains including civil and military aviation, driving, nuclear, power plant control room operation and air traffic control and cited in previous studies, like [15][17][16]. It is “being used as a benchmark against which the efficacies of other measures, theories or models are judged” [18]. The NASA-TLX uses a multi-dimensional scale to measure operator task performance, which consists of six subscales [13]: mental demand, physical demand, temporal demand, effort, performance and frustration level.

Workload Profile

The Workload Profile (WP) is a multidimensional subjective workload assessment instrument that is based on the multiple resource model proposed by Wickens (1987) [13][19][9]. This assessment tool uses data from eight dimensions on the demands imposed by a task: perceptual/central processing, response selection execution, spatial processing, verbal processing, visual processing, auditory processing, manual output and speech output. This method provides an overall rating for each task as well as a rating for each of the workload

dimensions. It uses a rating scale from 0 to 1 for each of the MWL dimensions. These multidimensional ratings should provide a good representation of MWL in order to diagnose the manner in which the task is demanding [19]. The workload profile method is the second subjective measure tool used in this research because it is based upon the sound underpinning theory of MRT, which is discussed in Section 2.3.2.

6.4.4 Physiological Workload Measures

Physiological workload measures are applied largely to the continuous measurement of physical responses of the human body [12]. An advantage of these measures is they are not obtrusive into the primary-task performance, but depending upon the collection method there may be a degree of physical constraint imposed [5]. The use of this measurement technique as an indicator of MWL is based upon the assumption that as task demand increases, changes in various participant physical responses are noticeable [13]. These physical responses can be measured with various bodily activity: cardiac, brain, respiratory, speech measures, and eye. Eye activity, specifically fixation duration, will be used to evaluate performance in this test environment. Fixations are moments when the eyes are relatively stationary, and is a measure of the amount of time the eye looks at a selected object [12]. When visual processing demands are high, operators tend to fixate longer [59]. So, increased fixation duration can be interpreted as an indicator of increased mental workload.

6.4.5 Performance

According to Miller (2001) most performance measures have the ability to estimate fluctuations in high levels of workload[12]. As cited by Cegarra and Chevalier (2008), studies have shown a correlation between poor performance in the main task and the mental workload experienced by participants[11]. The mental workload required in a given task can be assessed with performance metrics, such as time taken, speed, or number of errors [11]. Bubb (2005) defined human error probability (HEP) as the probability that a specific task under observation was accomplished defectively during a certain timeframe[30]. This experiment will use the HEP calculation as a measure of error. Mathematically, HEP is expressed as follows:

$$\text{HEP} = \frac{\text{number of observed errors}}{\text{number of the possibilites for an error}}$$

This study uses the Air Force MATB (Section 6.4.8) simulated environment to test the theoretical framework. The MATB simulation tracks performance errors and accuracy for each task. The experiment will focus on the system monitoring events as the measure of performance. This task was chosen because it has the largest number of scripted stimuli in the overall system. The number of incorrect responses to the stimuli divided by the number of total possible correct responses will be calculated for each subject.

6.4.6 Human Performance Modeling Approach

This research utilizes the Improved Performance Research Integration Tool (IMPRINT) as a human performance modeling tool using discrete event

simulation to predict mental workload. This tool was developed by the Human Research and Engineering Directorate (HRED) of the United States Army Research Laboratory (ARL) to evaluate human-system function allocation, human performance and mental workload estimation[44]. IMPRINT's primary domain has been in the military sector [35][46][47][48]; however, this research will extend the use of the tool in the civilian manufacturing sector. The initial step of the IMPRINT process is to identify the tasks that are necessary to operate the proposed system and the system operators to create the task network. In this framework, the inputs for step 1 were completed by using a Hierarchical Task Analysis (HTA) and Applied Cognitive Task Analysis (ACTA). The Hierarchical Task Analysis (HTA) provides inputs for the ACTA, Workload Profile, NASA-TLX and IMPRINT. The HTA is a step-by-step methodology, which was used to understand the task and procedure within this type of manufacturing environment. The HTA works by decomposing systems into a hierarchy of goals, sub-ordinate goals, operations and plans; it focuses on what the operator is required to do in terms of actions and/or cognitive processes to achieve a system goal [49]. The HTA was used to understand and examine process in order to provide inputs throughout the theoretical framework. The ACTA provided techniques, which can be used to analyze the mental demands required for each task. This methodology, compared to traditional task analysis, is most appropriate in exploring complex domains [43]. There are seven steps to the ACTA process, which are made up of four different methods: task diagram interview, knowledge audit interview, simulation interview and the cognitive demands table. Next, the order in which the tasks will be performed along with the times to perform the tasks must be established. This information was obtained from the HTA and Subject Matter Expert (SME)

interviews. All of this data is used to create the network diagram in IMPRINT. This study is made up of two scenarios: cleaning-inspection and final inspection; a network diagram was created for each scenario. The cleaning-inspection scenario model is made up of two primary functions, that run parallel, and twelve sub-functions. The final inspection scenario model is also made up of two primary functions that run parallel, but it has twenty-six sub-functions. To illustrate an example of the task network modeling, the final inspection scenario model is shown below (Figure 6.2 and 6.3):

Figure 6.2: Final Inspection: Overall MATB Model (Two Primary Tasks)

Figure 6.3: Final Inspection: Events Sub-Functions

Next, the numerical resource values are estimated for each task using the

IMPRINT rating scale; this is based upon the mental resources the operator needs to perform the task. The rating for each resource is based upon a scale (Appendix A) that contains anchors which describe the behaviors expected by each interval. Auditory, cognitive and fine motor resources are based upon a 7-point scale, speech is a 4-point scale, visual and gross motor demands are rated on a 6-point scale. After the resource ratings are entered, the software uses an embedded workload algorithm to calculate workload and provide workload values using charts and graphs over time for each system task (Appendix E).

IMPRINT can model different scenarios to study human capability relative to MWL predictions, in order to develop an effective human-system design that uses an ideal range of mental resources. Discrete events, with their estimated task times, and MRT ratings, for associated mental resources, are the simulation inputs. IMPRINT has a MWL element that defines workload relative to the MRT dimensions [36]. With this information, IMPRINT can formulate MWL predictions for varying task/design combinations. As IMPRINT does not provide guidance on how to mitigate mental overload to improve the system, the aim of this experiment is to model various scenarios based upon the IMPRINT predictions in order to improve the human-system design in the manufacturing domain. Based upon these predictions, the mental resource demands of these various scenarios will be mapped back to MRT. This study uses IMPRINT Pro Version 3.5.

6.4.7 Experiment Overview

The proposed research plan for assessing mental workload has one independent variable, task complexity. There are two levels for task complexity: cleaning-inspection (low task complexity) and final inspection (high task complexity). Next, the three MWL measurement categories of subjective,

physiological and performance, as cited by Cegarra and Chevalier (2008), are the dependent variables in this experiment. The dependent variables were measured with four different collection methods (Table 6.1). Two methods were used for data collection of the subjective measures: the NASA-TLX and Workload Profile. Fixation duration was collected using a nonintrusive eyetracking system to observe the physiological measure, and performance was calculated using the HEP formula from Section 6.4.5. JMP statistical analysis was utilized to analyze the experimental variables from the data collection. In summary, statistical analyses were performed on the various sources used to assess the different responses of mental workload associated with each level of task difficulty in a within subject experimental design.

Table 6.1: Experimental Variables

Type	Variable	Measure
Dependent	Subjective	NASA-TLX Scale
		Workload Profile Scale
	Physiological	Fixation Duration
	Performance	HEP
Independent	Task Complexity	Cleaning-Inspection
		Final Inspection

The experimental data from Table 6.1 is used to validate the theoretical framework that was designed to evaluate MWL demands in repetitive tasks operations. Each of the dependent variables are elements into the framework and measure MWL. These measures should not be statistically different within each task difficulty level. Therefore, the hypothesis is that the inputs to the framework will predict MWL in manufacturing. If the MWL measures indicate no significant difference amongst the measures for each task difficulty level, it

will be concluded that the model is valid in determining MWL.

6.4.8 Apparatus and Stimuli

Eyetracking

The method for collecting the physiological measures in this study is the Tobii – T120 eyetracker. This eyetracking system is integrated into a 17-inch TFT monitor with a resolution of 1280 X 1024 pixels. It can be used to record user gaze and visual physiological measures. The data collection frequency was 60Hz. This experiment took place in a controlled environment, the Human Performance and Cognition Laboratory at Wright State University to minimize error factors, like lighting and noise, because ambient lighting can affect the pupil, and noise can cause distractions and divert attention [5].

Air Force Multi-Attribute Task Battery Software (MATB)

The 2013 version of the Air Force Multi-Attribute Task Battery (AF-MATB) Software for human performance and workload research was utilized for data collection of each scenario. The MATB has been used in many human performance studies associated with multitasking like evaluating adaptive task allocation for automation monitoring (Parasuraman, Mouloua, & Molloy, 1996), task complexity [60] and the effects of medication [61]. It has also been used to evaluate single-task workload conditions [32].

The MATB was performed on a Dell Precision T5500 desktop computer with a 2.13GHz Intel processor and the Windows 7 Ultimate operating system. The Tobii eyetracking monitor was used to display the simulations. Participants interacted with MATB using a joystick and HP keyboard. MATB is a computer program

originally developed by NASA to evaluate human performance and workload in a multi-tasking environment [62]. It has recently been redeveloped by the United States Air Force[63].

The MATB is a simulated environment of general piloting tasks; the tasks are system monitoring, tracking, communications and resource management. It also provides scheduling and pump status displays. System monitoring is made up of two sub tasks: warning lights and scales. The normal state of the lights is that the left one is lit with a green light and the right one is dark. The participants are required to respond to the stimulus by clicking its corresponding function key when the left light goes dark or the right light turns red. Each scale has an indicator light that moves up and down independently on each scale. If the either of the indicator light moves more than one mark in either direction, the subject is required to hit its corresponding function key. The tracking task can operate in either manual or automatic mode. In the manual mode, the circular target will fluctuate outside the box, so the subject must use a joystick to keep it in the center of the inner box. However, during automatic mode, the target will remain in the inner box. For the communication tasks, the subject listens to messages on radio frequency changes, like air traffic control requests. When a message is given, the subject must respond to the content of the message; not all messages in the communication task may pertain to the subject. When a message is intended for the subject, the channels are changed using the up/down arrow keys on the keyboard and the frequency is changed by using the left/right arrows on the keyboard. Next, ENTER must be pressed when done selecting the frequency. The resource management component simulates the demands of managing the fuel system. The aim of this task is to maintain the two consumption tanks (Tank A

and Tank B) at a specific volume using the eight pumps and four supply tanks. In order to maintain the task objective, subjects must transfer fuel from the lower supply tanks to the consumption tanks. To activate a particular pump, the subject presses the pump number on the keyboard; pressing the key a second time will toggle the pump off. Fuel is transferred in the direction of the flow arrows. When the pump is red, the pump is not operational; this is a failed state. If the pump color matches the background color of the main window, it is a deactivated state. When the pump is on, the flowrate is listed at the pump status display; if the pump is off, flowrate is 0. The scheduling display provides information into the future for tracking and communication subtasks. The following (Figure 6.4) is a screenshot of the MATB display:

Figure 6.4: MATB Display

In this study, there were two task complexity levels pre-scripted that required monitoring of all MATB tasks: cleaning-inspection and final inspection.

The parameters for the cleaning-inspection and final inspection conditions were established by attempting to model the mental resource demands of a manufacturing process from a prior pilot study. The mental resources from the cleaning and final inspection models are incorporated into the MATB tasking design. The process flow of the framework (Figure 6.1) was followed to create the simulated conditions. The number of subtasks/events were manipulated to vary the load (Appendix C). Both conditions were set to a manual low tracking disturbance. The cleaning-inspection scenario contained one light detection event, one gauge fault and one shutoff valve. This composition of task repeated every 60 seconds. The final inspection scenario contained six light detection events, four gauge faults, three shutoff valves and four shutoff pumps. In the same manner as the cleaning-inspection scenario, the final inspection scenario tasks repeated every 60 seconds.

6.4.9 Participants

The study used eleven graduate students from the Biomedical, Industrial and Human Factors Department of Wright State University (WSU). The subject pool was made up of 4 females and 7 males. Sixty-four percent of participants were within the age range of 18 – 29. All participants had normal to corrected-to-normal vision; none were color deficient. The participants were assessed in a computer-based simulation environment, performing the MATB simulation. The Tobii eyetracking system was used to record user gaze and visual physiological measures while performing the experiment (Figure 6.5).

Immediately following each simulated scenario, the participants were asked to complete the NASA-TLX and Workload Profile questionnaires. Using assumptions from a previous MWL study, the GPower statistical tool was

Figure 6.5: MATB Display with Tobii Eyetracking System

utilized to calculate sample size[64]. According to the results, a minimum of seven subjects are required in order to obtain a statistical power of 0.84; a sample pool of eleven was achieved. A Latin-square design was used to randomize the experiment; half the subjects got the low complexity scenario first, and the others got the high complexity scenario first. The study was conducted in accordance to the Human and Subjects requirements specified by the Wright State University Internal Review Board (IRB). The subjects were volunteers and were not paid for their participation.

6.4.10 Experimental Procedure

A Workload Profile seminar was conducted and each subject was required to attend in order to participant in the experiment. Subsequently, each subject returned at an assigned time to participant in the experiment. The subjects were

given a consent form to review and sign for participating along with a pre-test questionnaire in order to obtain background information. Each participant received a short briefing on the experiment, equipment and procedures. Next, the Tobii eyetracking system was calibrated for each participant. A training session on the MATB was conducted for all subjects prior to running the simulation. Immediately following the training, the experiment took place. The experiment consisted of two treatments: cleaning-inspection and final inspection. The duration of each treatment was 10 minutes in length; every 60 seconds the same tasks repeated. After each scenario, the NASA-TLX and Workload Profile post-questionnaires were administered.

6.5 RESULTS

For each test run, data was collected to measure mental workload: NASA-TLX, WP, fixation duration and HEP. Table 6.2 summarizes the data collected.

Table 6.2: Response Variables Mean Summary

MATB Condition	Trial Order	Overall NASA-TLX (Rating Scale 0 to 100)		Overall WP (Rating Scale 0 to 8)		Fixation Duration (msec)		HEP %	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Cleaning-Inspection	1st	62.5000	8.1437	4.7200	0.5541	331.8000	30.4992	0.3900	0.1517
	2nd	55.2778	8.5905	3.8667	0.8664	418.5000	103.4809	0.3057	0.1021
	Overall	58.5606	8.8120	4.2545	0.8347	379.0909	88.1833	0.3364	0.1306
Final Inspection	1st	62.9167	8.6080	3.4875	1.5803	329.0000	48.1539	0.4246	0.1139
	2nd	69.5000	7.4675	4.7200	0.5070	294.6000	28.3425	0.2930	0.1322
	Overall	65.9091	8.4365	4.0477	1.3288	313.3636	42.4671	0.3528	0.1424

The data was analyzed using a t-test in JMP Pro 11 software for statistical

analysis to evaluate significant differences amongst the treatment levels. The significance level was fixed at 0.05. The normality assumption was tested for the response variables and the results showed no major departures from normal. The hypotheses for this test are as follows:

$$H_0 : \mu_1 = \mu_2 \qquad H_1 : \mu_1 \neq \mu_2$$

The null hypothesis assumes the mean MWL measures for the treatment levels are equal. However, the alternative hypothesis assumes the mean MWL measures amongst the treatments are different. This test was conducted to test whether the framework diagnoses a significant difference amongst the treatment levels. Table 6.3 summarizes the test results.

Table 6.3: t-Test Results

Response	t Ratio	p-value
NASA-TLX	1.997814	0.0298
Workload Profile	-0.43711	0.6666
Fixation Duration	-2.22272	0.9812
HEP%	0.282423	0.3903

The t-Test results (Table 6.3) show that the workload profile, fixation duration and HEP do not indicate a significant difference between the treatment levels of cleaning inspection (low complexity) and final inspection (high complexity). Therefore, the participants' responses did not vary significantly for the two task models.

Next, a correlation analysis was conducted to identify if a linear relationship exists between the MWL measures for each treatment level. This was done to test whether the framework identifies a linear relationship among the MWL measures for each treatment level. Table 6.4 summarizes the correlation results. Two of the three MWL categories (physiological and performance) were significantly correlated for each treatment level.

Table 6.4: Spearman's Correlation

Treatment Variable	<i>Low</i>		<i>High</i>	
	<i>rho</i>	<i>p</i>	<i>rho</i>	<i>p</i>
TLX - WP	0.51952	0.0132*	0.60641	0.0479*
TLX - Fixations	-0.2366	0.2886	0.27791	0.408
TLX - HEP	0.37394	0.0865	-0.09112	0.7899
WP - Fixations	-0.00537	0.9811	-0.05023	0.8834
WP - HEP	0.2599	0.2428	0.31507	0.3453
HEP - Fixations	-0.87627	<.0001*	-0.91818	<.0001*

* $p < 0.05$

Figure 6.6: IMPRINT Workload Profile for Cleaning-Inspection Model

Figure 6.7: IMPRINT Workload Profile for Final Inspection Model

Figures 6.6 and 6.7 illustrate the workload profile from IMPRINT for the 60 second work cycle of each experimental condition. Figure 6.6 shows the highest level of load is at the initiation of the cycle, then the load peaks again at about 40 seconds within the cycle at a value of 52.81 during a gauge triggered fault. The overall workload for this condition in IMPRINT averages 59.12. Similarly, as the low condition, Figure 6.7 demonstrates the workload profile for the final inspection scenario. A high level of load is experienced at the initiation of the simulation cycle. The model specifies that the workload spikes again at 30 seconds with a value of 156.49 and at 49 seconds with a value of 139.83, during both of these times, there are four overlapping tasks. The average overall workload for this condition in IMPRINT is 67.18.

Mental workload for each participant was evaluated using a comparison of high and low workload points from the IMPRINT mathematical model's

prediction. Table 6.5 shows these values for both processes. A second period around these points was used to calculate the fixation duration for each participant (Figure 6.8).

Table 6.5: IMPRINT MWL Predictions

Scenario	IMPRINT Profile	Overall MWL Value
Cleaning-inspection	low point	14.50
	high peak	52.81
Final Inspection	low peak	14.50
	high peak	156.49

Figure 6.8: Fixation Duration Corresponding to a High and a Low Point of the IMPRINT Model
(standard deviation represented with the error bars)

In order to perform this evaluation at a designated high point and low point in the mathematical model, the corresponding total fixation time was calculated (Figure 6.8). The purpose of this analysis was to validate the participant's physiological MWL indicator to the mathematical model. A t-Test was applied to the fixation duration measure to determine whether a significant difference occurs between the high and low points for each simulated task condition:

cleaning-inspection ($t\text{-Ratio} = 0.7389$, $p = 0.2349$) and final inspection ($t\text{ Ratio} = 1.7270$, $p = 0.0511$).

The simulation was designed using the theoretical framework to model the mental resource demands of a manufacturing process from a previous pilot study. The aim was to achieve the mental resource breakdown in Figures 6.9 and 6.10. The simulated process was designed with the greatest task load using cognitive, visual and fine motor resources.

Figure 6.9: Mental Resource Mapping for the Cleaning-Inspection Model

The WP ratings for both complexity conditions indicate that the task demands are greatest for the visual, manual and perceptual dimensions of the WP scale. The WP results correlate with the simulation design, validating that the operator's perceived task demands show a relationship with the design demands. Therefore, the WP subjective MWL method confirms that the simulated model mental demands are a result of the visual, cognitive and fine motor resources.

Figure 6.10: Mental Resource Mapping for the Final Inspection Model

6.6 CONCLUSIONS

This research presents a theoretical framework that provides a systematic approach to analyzing MWL in manufacturing. It incorporates Human Factors methods to evaluate MWL for human systems design and integration for manufacturing repetitive task operations. The first step in the analysis was to determine if the framework diagnosed a difference between the two task-levels (cleaning-inspection and final inspection models). The results showed that there was not a significant difference between the scenarios, relative to MWL, for three of the four response variables (Table 6.3). Although the final inspection model incorporated more stimuli, the participants' responses did not indicate a major change for mental workload. The next step of the analysis was to test the main hypothesis, which is the inputs to the framework will predict MWL in manufacturing for repetitive tasks. The premise of this hypothesis is that the inputs to the framework for each task complexity level tested would be significantly correlated. Two of the three input measures were significantly correlated. So, it is plausible to conclude that the framework accurately predicts overall MWL for repetitive task processes. A third analysis was performed to evaluate a comparison of the participants' physiological indicator and the IMPRINT mathematical model's prediction specifically at high and low MWL points in the task process. The results of the physiological indicator for the final inspection model show that there is a significant difference in the final inspection model's high and low points. This difference is likely due to the number of parallel subtasks that are required for this type of inspection process that uses the same type of resource. Therefore, the difference in the physiological measure between the high and low workload points concurs with the IMPRINT

predictions. On the other hand, results of the physiological indicator for the cleaning-inspection model show that there is not a significant difference in the final inspection model's high and low points, which could be attributed to both the low and high peaks are below the threshold measurement for manageable MWL. In summary, human performance modeling can be used to evaluate alternative processes that can be implemented based on MRT to ultimately improve MWL for the worker in the manufacturing environment.

The framework was validated using computer simulations, mathematical modeling and MWL measures. As part of the validation, two experimental scenarios with a MATB simulation were used, which varied in difficulty by the type and number of stimuli imposed on the operator. The key finding of the experiment is that the MWL inputs do not show a significant difference for the dependent variables of each task modeled. Therefore, the results support the hypothesis by accurately predicting MWL. The framework is robust, it is a combination of human factors methods and MWL metrics, which can be applied to any repetitive motion tasks, thereby enabling the transfer of the methodology to varying processes and systems. This theoretical framework uses MRT as the underpinning theory for the MWL predictions. Going forward, this work can be extended further by transitioning the approach into a practical application for industry, creating a MWL index as a quick reference for design predictions.

7 MENTAL WORKLOAD EVALUATION FOR HUMAN SYSTEMS DESIGN IN MANUFACTURING

7.1 ABSTRACT

Objective: This article evaluates the effectiveness of a proposed theoretical framework in measuring mental workload in repetitive task operations.

Background: As multitasking becomes more prevalent in manufacturing operations, mathematical models will be needed to understand the cognitive load on the operator in order to improve performance and safety.

Method: A human evaluation was conducted with twenty-six subjects in a simulated manufacturing experiment. Building blocks and measuring tools were used in a repetitive task with various treatment levels. The mental workload of each treatment was measured using subjective, physiological and performance measures.

Results: The key finding of this experiment is that the framework accurately predicts MWL as the inputs are statistically correlated for two of the three independent variables for each of the tasks modeled.

Conclusion: The theoretical framework was developed using a systematic

approach for measuring mental workload. The results support the hypothesis that the framework accurately predicts MWL and supports more than one measure is needed to predict MWL in repetitive tasks processes.

Application: The proposed framework was designed to evaluate operator mental workload utilization in the manufacturing domain to improve the design of modern manufacturing processes requiring high cognitive demand.

Key Words: Human Performance, Mental Workload, Manufacturing, Framework, Cognitive Ergonomics

7.2 INTRODUCTION

As the world becomes more competitive, production systems must become more flexible, adaptable, productive, cost and schedule efficient and quality driven, which requires a focus on the human operator [3]. Mental workload should be considered in the system design to ensure that high levels of MWL are within the worker's capability [65]. Lindblom & Thorvald (2014) addresses the question of how the understanding of cognitive load in manufacturing can lead to a better workplace for shop floor workers [1]. In this study, a framework is proposed using the theory of various Cognitive Work Environment Problems (CWEPs) to understand how task and work station designs influence an operator's cognitive load. In another study, Thorvald & Lindblom (2014) present the initial development of a cognitive load assessment tool for manufacturing operations [2]. The aim of this tool is to identify risk in tasks and workstation designs where a high cognitive load may lead to poor performance. The tool evaluates the task and workstation functions; it is made up of an evaluation form

to assess factors that can influence the task or workstation. These frameworks do not measure and compare MWL across the various categories: subjective, physiological and performance. This research proposes a theoretical framework using a combination of analytical and empirical techniques to evaluate MWL resources in manufacturing for repetitive task operations using the three categories of MWL in efforts to improve the diagnosticity of the framework. The aim of this framework is to improve operator performance and human-system design through the use of mental workload applications to identify operator mental workload utilization. The framework is illustrated as follows:

Figure 7.1: Theoretical Framework for Evaluating MWL

The above stated framework is made up of six primary steps. Step 1 is to study the manufacturing process and gain knowledge of the system. The tool used for this assessment was a Hierarchical Task Analysis (HTA). The HTA is a step-by-step methodology to understanding a task or system. It works by decomposing systems into a hierarchy of goals, sub-ordinate goals, operations and plans; it focuses on what the operator is required to do in terms of actions and/or cognitive processes to achieve a system goal [49]. Next, Multiple Resource Theory (MRT) is applied in step 2 to assess the mental resources

utilized to complete the process tasks. MRT is a predictive model that aids in understanding an operator's performance ability while multi-tasking [33]. When an individual performs a task, he or she expends mental operations and to some extent, each operation deploys mental processing resources crucial to completing the task [35]. People are capable of multi-tasking until task demands exceed available resources. According to MRT, the human mind can allocate several resources to task demands either individually or collectively to include: visual, auditory, cognitive, motor, and speech. When task demands overlap, fewer resources are available and MRT predicts that performance will degrade when multiple task requiring competing resources, which could lead to a compromise in system safety and effectiveness. Next, simulation modeling is deployed in Step 3; this step uses Improved Performance Research Integration Tool (IMPRINT). IMPRINT is a human performance modeling approach that uses computer-based discrete event simulation to predict mental workload. This tool was developed by the Human Research and Engineering Directorate (HRED) of the United States Army Research Laboratory (ARL) [44]. IMPRINT is used to quantify the expected MWL in the system design. Step 4 measures mental workload using subjective, performance and physiological measures. The subjective measure used is the National Aeronautics and Space Administration – Task Load Index (NASA-TLX). NASA-TLX is a subjective MWL assessment tool; it is the most commonly applied MWL assessment tool. The NASA-TLX uses a multi-dimensional scale to measure operator task performance, which consists of six subscales: mental demand, physical demand, temporal demand, effort, performance and frustration level [18]. With performance metrics, such as time taken, speed, or number of errors, the mental workload required in a given task can be assessed [11]. Bubb (2005) defined human error probability (HEP) as the

probability that a specific task under observation was accomplished defective during a certain timeframe [30]; the proposed framework uses this metric for performance assessment. The use of physiological measures as an indicator of MWL is based upon the assumption that as task demand increases, changes in various participant physical responses are noticeable [13]. Fixation count was used as the physiological measure. Fixations are moments when the eyes are relatively stationary. As cited [66] findings indicate that the frequency of long fixations increase with increased workload (Iqbal, Adamczyk, Zheng, & Bailey, 2004, 2005; Iqbal, Zheng, & Bailey, 2004; Lin, Zhang, & Watson, 2003; Rognin, Grimaud, Hoffman, & Zeghal, 2004; Stein, 1992; Van Orden, 2000; Van Orden et al., 2000; Veltman & Gaillard, 1998; Zeghal, Grimaud, Hoffman, & Rognin, 2002). Step 5 analyzes the data from Steps 3 and 4 to determine the MWL condition (i.e. overloaded or under-loaded). If there is a MWL overload, an analysis using MRT will be done to determine the attribution of mental resources that correlate to the mental overload and/or performance errors. (If a mental overload condition is not measured, the process can end.) In the event of a mental overload situation, step 6 will evaluate and revise the tasks. The manufacturing system can be modified based on the MRT principles to reduce the resources contributing to the mental overload, and MRT can be applied again to compare the modified system resources to the baseline.

The focus of this study is to develop and test the proposed framework, which utilizes a systematic approach for measuring mental workload in repetitive task operations, like manufacturing. The hypothesis of this study is that the inputs to the framework will predict operator MWL in a manufacturing environment. To test this hypothesis an experiment was designed and conducted

with the following treatment levels: assembly and inspection with tools (ATI), assembly with tools (AT), assembly and inspection (AI), and assembly only (A). These task combinations are representative of common manufacturing work procedures with varying levels of task complexity.

7.3 METHOD

7.3.1 Participants

The study was made up of twenty-six participants; 14 females and 12 males. Eighty-eight percent of participants were within the age range of 18 – 29. All participants had normal to corrected-to-normal vision; none were color deficient. Three subjects had previous production experience. The participants were assessed in a simulated manufacturing environment. The primary task in the experiment was to build an object with toy building blocks, in a repetitive process. The subjects were volunteers and not paid for participating. Prior to participating in the study, informed written consent was obtained from each subject. This study was conducted in compliance with the Wright State University Internal Review Board (IRB).

7.3.2 Apparatus and Stimuli

Tobii Pro Glasses 2 Eye Tracker was used to record the visual physiological measure while performing the experiment (Figure 7.2). These glasses are a non-intrusive method for measuring eye movement; the head unit weights approximately 0.1 pound. The raw fixation filter of 20 milliseconds was used to translate the gaze data into eye movements. The Tobii Pro Analyzer Version 1.16 software was employed to analyze fixation frequency and export videos

made with the Tobii glasses. The data collection frequency was 100 Hz. The Tobii Glasses Controller ran on a Dell Laptop with Windows 7.0 operating system.

Figure 7.2: Simulated environment with Tobii Eyetracking Glasses

7.3.3 Experimental Procedure

A within subject design was used in a repetitive task simulation using toy building blocks. Before the experiment began, each subject was given a briefing on the test scenarios and procedures. For each simulated scenario (i.e. treatment) the participants were given up to five minutes to review the work instructions (Appendix D) and train with the toy building blocks and inspection tools. The toy blocks were chosen to build with because of its similarity to an assembly process. During the simulation, the subjects had to adhere to a combination of color criterion and use a scale and caliper to take inspection measurements. There were different instructions for each test scenario. The color coding and measuring with tools were used to simulate inspection tasks. Next, the Tobii eyetracking

glasses were calibrated before data collection of each simulation. Immediately following the calibration, the experiment took place. Each scenario was given a targeted cycle time. Each cycle was completed five consecutive times during each treatment run. After completing each scenario, the NASA-TLX post questionnaire was administered.

There are three dependent and four independent variables in this experiment (Table 7.1). The process flow of the theoretical framework (Figure

Table 7.1: Experimental Variables

Type	Variable	Measure
Independent	Task Complexity	Assembly and Inspection with Tools (ATI)
		Assembly with Tools (AT)
		Assembly and Inspection (AI)
		Assembly only (A)
Dependent	Mental Workload	Subjective Physiological Performance

7.1) was applied to develop and examine the various conditions of the simulated processes. Each of the response variables for this experiment are elements in the theoretical framework. JMP statistical software package was used to analyze the response variables. The test scenarios were randomized using a Latin-square method.

7.3.4 Data Collection

Data was collected for each treatment to measure mental workload: NASA-TLX, fixation frequency, and HEP. Table 7.2 summarizes the collection.

Table 7.2: Descriptive Statistics for the Experimental Variables

MEASURE	Treatment	M	SD	min	max	range	95% CI	Effect Size
SUBJECTIVE								
NASA-TLX rating scale 0 - 100	ATI	60.87	14.51	24.17	90.83	66.66	[55.01, 66.72]	0.55
	AT	51.44	17.83	14.17	76.67	62.5	[44.24, 58.64]	
	AI	43.14	19.26	6.67	77.5	70.83	[35.36, 50.92]	
	A	30.75	18.44	0.33	59.17	58.84	[23.30, 38.2]	
PHYSIOLOGICAL								
Fixation Frequency	ATI	26408.96	8557.17	10139	53357	432189	[22,952.65, 29,865.28]	0.82
	AT	21621.35	6462.88	8949	35231	26282	[19,010.93, 24,231.76]	
	AI	11698.73	3846.47	5883	20010	14127	[10,145.11, 13,252.35]	
	A	5840.11	1854.31	1798	10846	9048	[5,091.14, 6,589.0881]	
PERFORMANCE								
HEP (%)	ATI	0.15	0.09	0.02	0.33	0.31	[0.12, 0.19]	0.11
	AT	0.16	0.11	0	0.525	0.525	[0.11, 0.20]	
	AI	0.16	0.12	0	0.48	0.48	[0.11, 0.21]	
	A	0.09	0.12	0	0.5	0.5	[0.04, 0.14]	

7.4 RESULTS

Table 7.3 reports the results of the repeated measures ANOVA comparing the means of the mental workload measures for the four treatments. The test hypotheses are as follows:

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = 0$$

$$H_1 : \mu_i \neq 0 \text{ for at least one } i$$

The null hypothesis assumes that all the MWL means across the four different treatments are the same. On the other hand, the alternative hypothesis assumes that at least one MWL measure differs from the others.

The data showed a significant effect on MWL for each treatment level at a significance level of 0.05 for all three of the measures: NASA-TLX, fixation frequency and HEP. Therefore, it is concluded that there is a significant difference

Table 7.3: Analysis of Variance Results

Measures	Source	df	SS	MS	F	<i>p</i>
TLX	Model	4	30340.49	7585.12	29.9819	<.0001
	Error	99	25046.01	252.99		
	Total	103	55386.50			
Fixations	Model	4	6.61E+09	1.65E+09	109.1059	<.0001
	Error	99	1.50E+09	1.51E+07		
	Total	103	8.11E+09			
HEP	Model	4	0.1433	0.03583	2.9534	0.0237
	Error	99	1.2011	0.012132		
	Total	103	1.3444			

between the treatments in the experiment. A post hoc test was performed to compare each treatment with all other treatments. The hypotheses for this test are:

$$H_0 : \mu_1 = \mu_2 \qquad H_1 : \mu_1 \neq \mu_2$$

The null hypothesis assumes that both MWL treatment means are the same. Otherwise, the alternative hypothesis assumes that the means are not equal. The data in Table 7.4 is a summation of the post hoc comparison using the Student's *t* test. This test indicated two of the three mean MWL measures were significantly different for five of the six treatment combinations. In addition, the HEP results do not imply a significant difference in performance for the inspection task treatment combinations. Subsequently, a correlation analysis (Table 7.5) was conducted to identify if a linear relationship exists between the MWL measures for each treatment level. Two of the three MWL measures (HEP and fixation frequency) were significantly correlated for each treatment level.

Table 7.4: Student's t Test results

Level	Level	p < 0.05		
		TLX	Fixations	HEP
AI	A	0.0061	<.0001	0.0139
AT	A	<.0001	<.0001	0.0237
ATI	A	<.0001	<.0001	0.0279
AI	ATI	<.0001	<.0001	
AT	ATI	<.0001	<.0001	
AI	AT		<.0001	

Table 7.5: Spearman's Correlation

Treatment Variable	ATI		AT		AI		A	
	rho	p	rho	p	rho	p	rho	p
Fixation - TLX	0.1329	0.5176	-0.2169	0.2873	0.0667	0.7462	0.418	0.0336*
HEP - TLX	-0.02	0.9226	-0.1106	0.6069	-0.0177	0.9316	0.3266	0.1034
HEP - Fixations	0.4705	0.0153*	0.4255	0.0382*	0.4905	0.011*	0.4829	0.0125*

* p < 0.05

For each treatment, data was collected to measure MWL: NASA-TLX, fixation frequency and HEP. An analysis was conducted to compare the effect of task complexity on mental workload in the four different treatments. There was a significant effect of task complexity on MWL (Table 7.3) for each treatment level. Two of the three mean MWL measures were significantly different for five of the six treatment combinations (Table 7.4). Only one MWL measure (i.e. fixation frequency) showed a significant difference between the AI and AT conditions. This implies that the subjects' perception and actual performance did not show a statistical difference between these two treatment levels. To evaluate this further, the resource scale (Appendix A) in IMPRINT was used to calculate the MWL resource utilization for all the treatments, and then graphed

(Figure 7.3). The treatments with the inspection elements utilized more cognitive resources in comparison to the assembly only treatment (A).

Figure 7.3: MRT Resource Utilization for Each Treatment

The difference in cognitive resource utilization (Table 7.6) between the AI and AT treatments is 32.7. This cognitive utilization difference is the lowest between any of the treatment combinations. This implies that the difference in utilization of cognitive resources was not large enough to effect the operators' perception or performance. This finding is similar to a study by Evans (2013); the findings of this experiment could not detect MWL differences between a fully automated and partially automated system using the three categories of MWL [67]. However, the measures were able to detect differences among a fully automated and manual task.

Table 7.6: Difference in Mental Resource Utilization

Level	Level	cognitive	fine motor	visual
AI	A	67.2	-4.4	42
AT	A	35.5	36.7	23.2
ATI	A	113.7	36.9	67.1
AI	ATI	-45.5	-41.3	-25.1
AT	ATI	-78.2	-0.2	-43.9
AI	AT	32.7	-41.1	18.8

7.5 DISCUSSION

Each step of the process was important to determining whether the framework accurately predicts MWL. Figure 7.4 summarizes the steps taken to analyze the data collection.

Figure 7.4: Analysis Approach

In step 1, the data collection was summarized using descriptive statistics to

describe the data. The mean MWL responses for the NASA-TLX and fixation frequency showed the same trend across treatment levels. On the other hand, HEP showed the AI and AT treatments had similar values. Next, step 2 uses an F-test statistic to compare the means of each MWL level across the four treatment levels. This was done to determine whether the framework could diagnose a significant difference amongst the treatments for each task complexity level. The results in table 7.3 showed that there is a significant difference amongst the treatments for each MWL response for at least one of the treatment levels. Afterwards, a post hoc test using the Fisher's Least Significant Difference (LSD) method was performed to test whether the framework diagnoses a difference in treatment combinations in step 3. Two of the three MWL measures indicated a significant difference across all of the combinations except one, AI-AT combination (see table 7.4). This may be due to the fact that the treatment combination (AI-AT) experienced the lowest cognitive and visual utilization difference of any of the other combinations. This trend was also shown in the descriptive statistics. Step 4 administered a correlation test to determine if a linear relationship exists among the MWL measures in the framework for each treatment. If the MWL measures indicate a significant correlation amongst the measures for each task difficulty level, it will be concluded that the framework is valid in predicting MWL. The two measures, fixation and HEP, that were statistically correlated for each treatment level, are objective, in comparison to the NASA-TLX, a subjective measure. During step 5, the MWL resources for each treatment were further examined to compare the resource utilization across each treatment combination. The resource mapping from IMPRINT indicated the tasks with the inspection elements created the highest cognitive load for the operators. The results of this work demonstrate

the influence of inspection tasks on the operator during a manual procedure. Although the simulated task would be considered fairly simple, when the inspection elements were added, the cognitive load of the operator increased and performance declined.

7.6 CONCLUSIONS

System design and procedures in manufacturing must be approached differently to improve performance as multitasking is becoming an integral part of production processes. The system design of tasks that require simple routine procedures must be approached differently than tasks with higher cognitive load, in order to sustain required levels of performance. Eklund (2000) demonstrates a relationship between workers' job characteristics, which include physical, physiological, cognitive and other organizational factors, with its quality and productivity performance [68]. The proposed framework in this study offers an alternative for system design in manufacturing. Bommer and Fendley (2015) introduced this framework during a pilot study [69]. Since, that time, the theoretical framework has been expanded and validated in a laboratory setting, which warrants merit for future work and validation in the field.

This study simulated a manual repetitive manufacturing process with inspection tasks. The results of this work demonstrated the influence of inspection tasks on the operator during a manual procedure. Although the simulated task would be considered quite simple, when the inspection elements were added the cognitive load of the operator peaked. An extended study, using this framework, designed to develop a regression model as a tool for practical application of optimizing the cognitive load for improved performance could

benefit the manufacturing industry. In closing, the proposed framework offers an innovative approach in manufacturing for human systems design; it incorporates cognitive design into the manufacturing process. This work is relevant to the changing demands of the manufacturing industry.

8 THEORETICAL CONTRIBUTIONS AND PRACTICAL APPLICATION

As manufacturing operations move towards more complex systems and procedures to become more competitive and adaptive to production demands, cognitive demands are becoming a predominate factor in manufacturing operations. Therefore, cognitive models are needed to analyze the operator's performance as it relates to mental workload while performing repetitive task operations. Theoretical frameworks to support the development of these cognitive models are required to provide a better understanding of the human-system interaction that impacts operators' mental workload.

1. IMPRINT Application

This study is one of the first to apply IMPRINT in a non-military application. Future studies to establish a MWL threshold for repetitive manual tasks would benefit the manufacturing industry for creation of improved model prediction.

2. Capacity Planning

The findings of the pilot study in this work demonstrate that the proposed framework could be used during design and set-up stages of a process to construct better operations in efforts to reduce mental overload for the

operator in repetitive task processes. When looking at the results of this pilot study, this model has proven to be valuable for understanding operator MWL resources in human-machine design for capacity planning of process set-up for a system that is not built, and modifications for an existing system. This method can improve the design of modern manufacturing processes requiring high cognitive demand.

3. Supervisory Control Tasks

Experiment 1 tested the proposed framework in a supervisory control task. The framework was validated using computer simulations, mathematical modeling and MWL measures. The findings support that the theoretical framework accurately predicted MWL. This work is important because, as manufacturing systems become more automated, the cognitive demand of the operator must be included in the system design for improved performance. Therefore, industry could benefit from future studies that model various manufacturing supervisory controlled processes to further examine these findings.

4. Manual and Inspection Tasks

Experiment 2 simulated a manual repetitive manufacturing process with inspection tasks. The results of this work demonstrated the influence of inspection elements on the operator during a manual procedure. Although the simulated task would be considered quite simple, when the inspection elements were added, the cognitive load of the operator peaked. An extended study, using this framework, designed to develop a regression model as a

tool for practical application of optimizing the cognitive load for improved performance could benefit the manufacturing industry.

In closing, the proposed framework offers an innovative approach in manufacturing for human systems design; it incorporates cognitive design into the manufacturing process. This work is relevant to the changing demands of the manufacturing industry and can be applied across domains with repetitive task processes.

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APPENDIX A: MRT Resource Rating Scale in IMPRINT

Speech Resource Demand Values

Automatic Speech Demand Values	
Value	Automatic Demand
0.0	Nothing
2.0	Simple (1-2 Words)
4.0	Complex (Sentence)

Visual Resource Demand Values

Automatic Visual Demand Values	
Night Vision Goggles: Without Night Vision Goggles	
Value ▲	Automatic Demand
0.0	Nothing
1.0	Register/Detect (Detect Occurrence of Image)
3.0	Inspect/Check (Discrete Inspection/Static Condition)
4.0	Locate/Align (Selective Orientations)
4.4	Track/Follow (Maintain Orientation)
5.0	Discriminate (Detect Visual Differences)
5.1	Read (Symbol)
6.0	Scan/Search Monitor (Continuous/Serial Inspection)

Auditory Resource Demand Values

Automatic Auditory Demand Values	
Value ▲	Automatic Demand
0.0	Nothing
1.0	Detect/Register Sound (Detect Occurrence of Sound)
2.0	Orient to Sound (General Orientation/Attention)
3.0	Interpret Semantic Content(Speech) Simple (1-2 Words)
4.2	Orient to Sound (Selective Orientation/Attention)
4.3	Verify Auditory Feedback (Detect Occurrence of Anticipated Sound)
6.0	Interpret Semantic Content(Speech) Complex (Sentence)
6.6	Discriminate Sound Characteristics(Detect Auditory Difference)
7.0	Interpret Sound Patterns (Pulse rates etc.)

Cognitive Resource Demand Values

Automatic Cognitive Demand Values	
Value ▲	Automatic Demand
0.0	Nothing
1.0	Automatic (Simple Association)
1.2	Alternative Selection
4.6	Evaluation/Judgement (Consider Single Aspect)
5.0	Rehearsal
5.3	Encoding/Decoding, Recall
6.8	Evaluation/Judgement (Consider Several Aspects)
7.0	Estimation, Calculation, Conversion

Fine Motor Resource Demand Values

Automatic Fine Motor Demand Values	
Value ▲	Automatic Demand
0.0	Nothing
2.2	Discrete Actuation (Button Toggle Trigger)
2.6	Continuous Adjustive (Flight Control, Sensor Control)
4.6	Manual (tracking)
5.5	Discrete Adjustment (Rotary, Vertical Thumb Wheel, Lever Position)
6.5	Symbolic Production (Writing)
7.0	Serial Discrete Manipulation (Keyboard)

APPENDIX B: Pilot Study Cognitive Analysis

Task Diagram

Purpose: To obtain a broad overview of the task

Purpose: To identify those task steps that require the most cognitive skills

Operator Experience: 2 years

Date: 12/17/2014

Question: Think about what you do when performin this task, can you break down this task into less than six, but more than three steps?

Which of the steps require difficult cognitive skills?

Step	Judgements	Assessments	Problem Solving/Thinking
1 Mix Acid	e.g. which beakers to use	e.g. mixtures at correct levels	
2 Prepare Part	e.g. positioning of parts	e.g. good or bad parts	e.g. how to correct contamination
3 Prepare Paperwork			
4 Clean Slides	e.g. broken or chipped		e.g. can you use slide or throw it away
5 Clean Beakers	e.g. condition of the beaker	e.g. amount of water/chemical to use	
6 Run Parts	e.g. inspection of parts	e.g. inspection critena	e.g. whether a defective part can be fixed or cutout

Task Diagram

Purpose: To obtain a broad overview of the task

Operator Experience: 4 years

Date: 12/18/2014

Purpose: To identify those task steps that require the most cognitive skills

Question: Think about what you do when performin this task, can you break down this task into less than six, but more than three steps?

Which of the steps require difficult cognitive skills?

Step	Judgements	Assessments	Problem Solving/Thinking
1 Dip Platinum sheet in IPA to remove contamination. Next, place in holding tank.		e.g. time and chemical levels	
2 Dip in chemicals.		e.g. track time	
3 Water rinse			
4 Back in IPA			
5 Dry on the rack. Once dry place between two slides.	Meet standard or not		
6 Final inspection under microscope	e.g. good or bad, meet spec.		e.g. make repairs

Task Diagram

Purpose: To obtain a broad overview of the task

Purpose: To identify those task steps that require the most cognitive skills

Operator Experience: 1 year

Date: 12/18/2014

Process: B

Question: Think about what you do when performin this task, can you break down this task into less than six, but more than three steps?

Which of the steps require difficult cognitive skills?

Step	Judgements	Assessments	Problem Solving/Thinking
1 Focus part under the microscope	e.g. scope in focus or not		e.g. get instrument in focus
2 Pin part with gauge	e.g. whether gauge properly placed	e.g. whether gauge passes inspection point	e.g. whether to pass or kick-out part
3 inspect part for defects	e.g. compare to inspection criteria		
4 Remove spatter			e.g. make proper repair/determine if meets standard
5 Check for bent part	e.g. compare to inspection criteria		
6 Fill out inspection sheet	e.g. documentation		

Task Diagram

Purpose: To obtain a broad overview of the task

Operator Experience: 4 years

Date: 12/18/2014

Purpose: To identify those task steps that require the most cognitive skills

Process: B

Question: Think about what you do when performing this task, can you break down this task into less than six, but more than three steps?

Which of the steps require difficult cognitive skills?

Step		Judgements	Assessments	Problem Solving/Thinking
1	Inspect mandrel hole	e.g. is mandrel inserted all the way		
2	Check cuplar	e.g. Is it round, complete circle		
3	Inspect weld	e.g. pitted, cracks, discoloration		
4	Clean spatter	e.g. good or no good		

Knowledge Audit
 Purpose: To identify instances where expertise are used and what sort of expertise is used

Operator Experience: 2 years
 Date: 12/17/2014

	Aspect of Expertise	Cues and Strategies
Past and Future Is there a time when you walked into the middle of the task and knew exactly how things got there and where they were headed?	Yes, someone skipped a step and was able to identify it quickly.	No cues, just experience led to the finding
Big Picture What are the major elements that you have to know and keep track of?	1) Track part ordering for traceability 2) Lot #s 3) Process timing to meet spec. (possible to burn a part) 4) Chemicals - make sure right mixtures 5) Supplies - can't run without beakers and slides 6) Quality inspection points	
Noticing Have you had experiences where part of the job "popped out at you"; where you noticed things going on that others did not catch? Example?	n/a	
Job Smarts When you do this task, are there ways of working smarter or improvising accomplishes more with less that you have found especially useful?	Can't change or skip a step during prost processing because of product requirements	
Opportunities/Improvising Can you think of an example when you have improvised in this task or noticed an opportunity to do something better?		
Self Monitoring Can you think of a time when you realized that you would need to change the way our were performing in order to get the job done? Example?	To eliminate wait time in the process, changed the order of cleaning slides and paperwork	Clean slides first because they have to dry, once cleaned then start paperwork
Anomalies Can you describe an instance when you spotted a deviation from the norm, or knew something was amiss?	A beaker wasn't calibrated	quality control sticker was removed
Equipment Difficulties Have there ever been times when you had to rely on experience to avoid being led astray by the equipment?	Equipment settings (e.g. the ultrasonic machine sounds a certain way when operating correctly)	

Knowledge Audit
 Purpose: To identify instances where expertise are used and what sort of expertise is used

Operator Experience: 4 years
 Date: 12/18/14

	Aspect of Expertise	Cues and Strategies
Past and Future Is there a time when you walked into the middle of the task and knew exactly how things got there and where they were headed?	Everything is dummy proofed; if out of sink, it pops out	
Big Picture What are the major elements that you have to know and keep track of?	1. Good/Bad parts (i.e. part inspection. 2. Tracking time in process 3. Follow process and procedure (understanding) 4. Details -- problems and defects.	
Noticing Have you had experiences where part of the job "popped out at you"; where you noticed things going on that others did not catch? Example?	Incident where the part traceability was missing.	Repeat the same routine
Job Smarts When you do this task, are there ways of working smarter or improvising accomplishes more with less that you have found especially useful?	Work in U-shape workcell, do not get steps out of order	
Opportunities/Improvising Can you think of an example when you have improvised in this task or noticed an opportunity to do something better?		
Self Monitoring Can you think of a time when you realized that you would need to change the way our were performing in order to get the job done? Example?	The way repairs were being managed.	
Anomalies Can you describe an instance when you spotted a deviation from the norm, or knew something was amiss?		
Equipment Difficulties Have there ever been times when you had to rely on experience to avoid being led astray by the equipment?	Element was blown out in the hot plate (knew from experience)	

Knowledge Audit

Operator Experience: 1 yr

Purpose: To identify instances where expertise are used and what sort of expertise is used

Date: 12/18/14

Process: B

	Aspect of Expertise	Cues and Strategies
Past and Future Is there a time when you walked into the middle of the task and knew exactly how things got there and where they were headed?		
Big Picture What are the major elements that you have to know and keep track of?	1) job numbers 2) part quantities 3) inspection criteria and measurements 4) follow job process flow	job instructions
Noticing Have you had experiences where part of the job "popped out at you"; where you noticed things going on that others did not catch? Example?	1) batch of parts cocked at an angle (do not check for angle position) 2) parts would not pin too much spatter	1) part looked abnormal 2) part passed the pin gauge, but looked out of norm
Job Smarts When you do this task, are there ways of working smarter or improvising accomplishes more with less that you have found especially useful?	Not really, not required to go in a certain order, find your own rhythm	inspection instructions are specific
Opportunities/Improvising Can you think of an example when you have improvised in this task or noticed an opportunity to do something better?		
Self Monitoring Can you think of a time when you realized that you would need to change the way our were performing in order to get the job done? Example?	Take frequent breaks because eyes get heavy (strained); mental and shoulder fatigue	job becomes uncomfortable; body can feel it coming on
Anomalies Can you describe an instance when you spotted a deviation from the norm, or knew something was amiss?	found tubes missing bumper from previous process	visual inspection
Equipment Difficulties Have there ever been times when you had to rely on experience to avoid being led astray by the equipment?	no; microscope in focus or not, pin gage is measured on laser mic. (mics are calibrated regularly)	

Knowledge Audit

Operator Experience: 4 years

Purpose: To identify instances where expertise are used and what sort of expertise is used

Date: 12/18/14

Process: B

	Aspect of Expertise	Cues and Strategies
Past and Future Is there a time when you walked into the middle of the task and knew exactly how things got there and where they were headed?	No.	Color coded and labeled
Big Picture What are the major elements that you have to know and keep track of?	Depends upon the part	Inspection Criteria
Noticing Have you had experiences where part of the job "popped out at you"; where you noticed things going on that others did not catch? Example?	Parts were welded wrong. (Ran by an engineer who does not normally run job.)	Just knew it from experience. Referred back to inspection docs.
Job Smarts When you do this task, are there ways of working smarter or improvising accomplishes more with less that you have found especially useful?	No. Really can't make any changes because all steps are critical.	
Opportunities/Improvising Can you think of an example when you have improvised in this task or noticed an opportunity to do something better?		
Self Monitoring Can you think of a time when you realized that you would need to change the way our were performing in order to get the job done? Example?	Must keep work station ergonomically correct	Pain in the shoulders and upper back; can feel yourself slumping
Anomalies Can you describe an instance when you spotted a deviation from the norm, or knew something was amiss?	Spotted an extra hole in a part.	Was following the inspection criteria
Equipment Difficulties Have there ever been times when you had to rely on experience to avoid being led astray by the equipment?	The smartscope could give false readings if not set correctly.	Measurement output would indicate a problem

Simulation Interview

Purpose: To determine the cognitive processes involved during the task under analysis within context of an incident

What errors would an inexperienced person be likely to make in this situation?

#	Event	Actions	Assessment	Critical Cues	Potential Errors
1	To make cleaning solution	Use and mix chemicals	Can use test strips to check chemical type	Chemical label	Could mix the wrong chemical Can cause chemical reaction, possible explosive
2	To clean parts	Set-up the ultrasonic tank	Digital readout on the machine		Wrong setting (i.e. timer)
3	To clean slides	Inspect slide for defect Scrub with soap and water	Inspect slide under magnifying glass	Results of the microscope inspection	The Smart Scope will reject the part if dirty (i.e. loss of time)
4	To inspect parts	Follow work and inspection instructions	Use inspection instruction list as reference	None; requires 100% inspection	Fail Smart Scope inspection Defect received at customer
5	To check diagnostic measurements	Verify measurement report	Check diagnostics data for correct measurements	Must meet spec.	Defect passed to the next process
6	To label parts container	Use marker to label parts container	Visual inspect labeling with traceability data before shipping	None; requires 100% inspection	Effects inventory control
7	To label shipping container	Use marker to label shipping container	Visual inspection	None; requires 100% inspection	Passed to next process
8					

Operator Experience: 2 years

Date: 12/17/2014

Simulation Interview

Purpose: To determine the cognitive processes involved during the task under analysis within context of an incident

What errors would an inexperienced person be likely to make in this situation?

#	Event	Actions	Assessment	Critical Cues	Potential Errors
1	Will not remove all the spatter to standards				Get to the customer, receive a CAPA (corrective action)
2	Miss defects in the inspection process	Follow the inspection criteria	Visual through the microscope	Rely on expertise to understand and know the inspection criteria	Out of standard parts could get to the customer; fatal, because part is implanted into people
3					

Operator Experience: 4 years

Date: 12/18/14

Process: B

Simulation Interview

Purpose: To determine the cognitive processes involved during the task under analysis within context of an incident

What errors would an inexperienced person be likely to make in this situation?

#	Event	Actions	Assessment	Critical Cues	Potential Errors
1	Mixed wrong chemicals	mixing solution	labelled and color coded	Process and procedure book	
2	Chemical spills	mixing solution	labelled and color coded	Process and procedure book	
3	Chemical accident	mixing solution	labelled and color coded	Process and procedure book	splash in eye, get it on hands; can cause chemical burns
4	No good inspection	poor judgement	inspection criteria	visual aids	get to the customer
5	Wrong traceability numbers	does the container number match the part number			inventory control
6	Missed process steps	Cannot skip steps		steps are numbered	cause scrap
7	Data sheets filled out incorrectly				could cause wrong repair, increase scrap rate
8					

Operator Experience: 4 years

Date: 12/18/14

Simulation Interview

Purpose: To determine the cognitive processes involved during the task under analysis within context of an incident

What errors would an inexperienced person be likely to make in this situation?

#	Event	Actions	Assessment	Critical Cues	Potential Errors
1	To know the inspection criteria (e.g. able to identify crack weld)	follow set-up sheets	visual inspection under microscope	visual aids	1) defect gets to customer 2) could kill someone
2	To know the proper process set-up and flow	place material in correct trays	follow work instructions	color coding and labeling	incomplete part could pass
3	To master the rhythm of the inspection process	1) put pin in hole 2) scrap spatter	inspection criteria	visual aids	1) damage part 2) keeping up with next process
4					
5					

Operator Experience: 1 year

Date: 12/16/14

Process: B

APPENDIX C: Experiment #1 MATB Parameters

Low Complexity Task - MATB Parameters

Condition Name	Condition Length	Communications Subtask		Tracking Subtask	System Monitoring Subtask			Resource Management Subtask			Subtask Component Visibility	
Low	Seconds	True Comms	False Comms	Difficulty	Automation	Lights	Gauges	Automation	Failures	Shut-offs	Task Window	Hidden
Low	60	0	0	Tracking Low	None	1	1	None	0	1	System Monitoring	☐

High Complexity Task - MATB Parameters

Condition Name	Condition Length	Communications Subtask		Tracking Subtask	System Monitoring Subtask			Resource Management Subtask			Subtask Component Visibility	
High	Seconds	True Comms	False Comms	Difficulty	Automation	Lights	Gauges	Automation	Failures	Shut-offs	Task Window	Hidden
High	60	0	0	Tracking Low	None	6	4	None	3	4	System Monitoring	☐

APPENDIX D: Experiment #2 Work Instructions

Task ATI Work Instructions

Step	Description	Picture	Critical Points
1	Hit lap button on stopwatch to start cycle		
2	Pick and place a block		The block must have eight holes.
3	Use a scale to measure the distance of the star label from the top tip of the star to the right edge of the block. The sticker must be 32 mm (+/- 2 mm) from the right edge. If it is not within spec, reject it to the scrap bin and choose another block.		Record dimension on log sheet.
4	Attach a block with four holes.		The block must be attached to the far right.
5	Attach a block with four holes.		<ul style="list-style-type: none"> a) Make sure the blocks are properly aligned. b) These two blocks must be different colors. c) Pink cannot be matched with green. d) Yellow cannot be matched with green. e) Orange cannot be matched with blue.
6	Attach a flat half-height eight-hole block offset by one row of holes.		<ul style="list-style-type: none"> a) The block must be a half-height block. b) Make sure this block is securely fastened to the bottom two blocks. c) Yellow blocks cannot be stacked on green blocks.
7	Attach an eight-hole block.		<ul style="list-style-type: none"> A) Orange cannot stack on blue. B) Orange blocks cannot stack on a yellow block. C) Blue cannot stack on green.

Task ATI Work Instructions (continued)

8		<p>The block must be placed in a vertical position.</p>
9		<p>A) Yellow blocks cannot be stacked on a green block. B) Pink cannot stack on green. C) Brown blocks cannot be stacked on yellow blocks. D) Brown cannot stack on red. E) Pink blocks cannot be stacked on red blocks. F) Pink cannot stack on green.</p>
10		<p>A) Green blocks cannot be stacked on a yellow block. B) Yellow blocks cannot be stacked on red blocks. C) Brown blocks cannot be stacked on yellow blocks. D) Orange cannot stack on blue.</p>
11		<p>Nine parts must be present in the correct location with all parts securely attached.</p> <p>Orange cannot be stacked on blue.</p>
12		<p>Use a caliper to measure the dimension of the hole under the overhang of the sloping block.</p> <p>Write the dimension on the log sheet</p>
13		<p>a) Mark two X's to the front side at the joint locations designated with a black dot.</p> <p>b) Mark three X's to the back side at the joint locations designated with a black dot.</p> <p>Correct location of the X's is critical</p>
14		<p>Place two stickers on the slope, the stickers should be 5 mm apart. Record measurement.</p> <p>Measure distance and record measurement on log sheet.</p> <p>Record</p>

Task AT Work Instructions

Step	Description	Picture	Critical Points
1	Hit lap button on stopwatch to start cycle		
2	Pick and place a block		The block must have eight holes.
3	Use a scale to measure the distance of the star label from the top tip of the star to the right edge of the block. The sticker must be 32 mm (+/- 2 mm) from the right edge. If it is not within spec, reject it to the scrap bin and choose another block.		Record dimension on log sheet.
4	Attach a block with four holes.		The block must be attached to the far right.
5	Attach a block with four holes.		Make sure the blocks are properly aligned.
6	Attach a flat half-height eight-hole block offset by one row of holes.		a) The block must be a half-height block. b) Make sure this block is securely fastened to the bottom two blocks.
7	Attach an eight-hole block.

Task AT Work Instructions (continued)

8	Attach a two-hole block to the far left end.		The block must be placed in a vertical position.
9	Attach a four-hole block.
10	Attach a four hole block.
11	Attach a four hole piece with a sloping end.		Nine parts must be present in the correct location with all parts securely attached.
12	<p>Use a caliper to measure the dimension of the hole under the overhang of the sloping block.</p> <p>Write the dimension on the log sheet</p>

Task AI Work Instructions

Step	Description	Picture	Critical Points
1	Hit lap button on stopwatch to start cycle		
2	Pick and place a block		The block must have eight holes.
3	Attach a block with four holes.		The block must be attached to the far right.
4	Attach a block with four holes.		<ul style="list-style-type: none"> a) Make sure the blocks are properly aligned. b) These two blocks must be different colors. c) Pink cannot be matched with green. d) Yellow cannot be matched with green. e) Orange cannot be matched with blue.
5	Attach a flat half-height eight-hole block offset by one row of holes.		<ul style="list-style-type: none"> a) The block must be a half-height block. b) Make sure this block is securely fastened to the bottom two blocks. c) Yellow blocks cannot be stacked on green blocks.
6	Attach an eight-hole block.		<ul style="list-style-type: none"> A) Orange cannot stack on blue. B) Orange blocks cannot stack on a yellow block. C) Blue cannot stack on green.
7	Attach a two-hole block to the far left end.		The block must be placed in a vertical position.

Task AI Work Instructions (continued)

8 Attach a four-hole block.		<p>A) Yellow blocks cannot be stacked on a green block. B) Pink cannot stack on green. C) Brown blocks cannot be stacked on yellow blocks. D) Brown cannot stack on red. E) Pink blocks cannot be stacked on red blocks.</p>
9 Attach a four hole block.		<p>A) Green blocks cannot be stacked on a yellow block. B) Yellow blocks cannot be stacked on red blocks. C) Brown blocks cannot be stacked on yellow blocks. D) Orange cannot stack on blue.</p>
10 Attach a four hole piece with a sloping end.		<p>Nine parts must be present in the correct location with all parts securely attached.</p> <p>Orange cannot be stacked on blue.</p>

Task A Work Instructions

Step	Description	Picture	Critical Points
1	Hit lap button on stopwatch to start cycle		
2	Pick and place a block		The block must have eight holes.
3	Attach a block with four holes.		The block must be attached to the far right.
4	Attach a block with four holes.		Make sure the blocks are properly aligned.
5	Attach a flat half-height eight-hole block offset by one row of holes.		a) The block must be a half-height block. b) Make sure this block is securely fastened to the bottom two blocks.
6	Attach an eight-hole block.
7	Attach a two-hole block to the far left end.		The block must be placed in a vertical position.

Task A Work Instructions (continued)

- 8 Attach a four-hole block.

- 9 Attach a four hole block.

- 10 Attach a four hole piece with a sloping end.

Nine parts must be present in the correct location with all parts securely attached.

APPENDIX E: Experiment #2 IMPRINT Output

Task ATI Workload Details

IMPRINT Operations Model Report Operator Workload Detail

Analysis Version: Assembly_Task ATI

Clock	Task Name	Overall Workload
00:00:00.00	1: Hit lap button on stopwatch to start cycle	4.20
00:00:01.00	2: Pick and Place an eight-hole block	34.56
	Confirm Block Holes	
00:00:02.70	3: Use scale to measure label	10.80
00:00:06.36	Write dimension on log sheet	12.80
00:00:09.36	4: Attach a block with four holes	32.26
	Confirm Block Holes1	
00:00:11.16	Check placement of block to the far right.	7.60
00:00:11.46	Spec. Orange cannot be matched with blue	201.28
	Spec. Yellow cannot be matched with green1	
	5: Attach a four-hole block	
	Confirm Block Type	
	Spec. Pink cannot be matched with green	
00:00:11.76	5: Attach a four-hole block	4.40
00:00:13.77	Check Block Alignment	7.60
00:00:14.08	6: Attach a flat half-layer block	75.96
	Confirm block height	
	Spec.: Green blocks cannot stack on yellow	
00:00:17.20	Confirm the block is securely fastened to bottom blocks	6.20
00:00:17.50	7: Attach an eight-hole block	201.28
	Confirm Block Holes2	
	Spec.: Orange cannot stack on blue	
	Spec: Blue cannot stack on green	
	Spec: Orange cannot stack on yellow	
00:00:20.65	8: Attach a two-hole block to the far left end	25.36
	Confirm Block Holes4	
00:00:23.96	Confirm block is placed in a vertical position	7.60
00:00:27.27	9: Attach a four hole block	412.76
	Confirm Block Holes5	
	Spec Pink cannot stack on green	
	Spec Pink cannot stack on red2	
	Spec. Brown cannot stack on yellow	
	Spec.: Brown cannot stack on red	
	Spec.: Green cannot stack on yellow	
00:00:28.40	10: Attach a four hole block	297.60
	Confirm Block Holes6	
	Spec. Brown cannot stack on yellow1	
	Spec. Green cannot stack on yellow	
	Spec. Orange cannot be stacked on blue	
	Spec. Yellow cannot stack on red	
00:00:29.43	11: Attach a four-hole block with a sloping edge	65.16
	Confirm Block Holes7	
	Spec. Orange cannot stack on blue	
00:00:32.03	Check for all nine parts in the correct location and securely attached	7.60
00:00:32.33	12: Use caliper to measure overhang hole	8.30
00:00:35.33	15: Write dimension on log sheet	12.80
00:00:39.26	13: Place an X on front two joints.	30.08
	Confirm joint location (critical)	
00:00:41.99	13: Place X on back three joints	30.08
	Confirm joint location (critical)1	
00:00:44.99	Add stickers, estimate and measure	13.20
00:00:50.29	15: Write dimension on log sheet1	12.80

Task AT Workload Details

IMPRINT Operations Model Report Operator Workload Detail

Analysis Version: Assembly_Task AT

Clock	Task Name	Overall Workload
00:00:00.00	1: Hit lap button on stopwatch to start cycle	4.20
00:00:01.00	2: Pick and Place an eight-hole block	34.56
	Confirm Block Holes	
00:00:02.70	3: Use scale to measure label	10.80
00:00:06.36	Write dimension on log sheet	12.80
00:00:09.36	4: Attach a block with four holes	75.96
	Check placement of block to the far right.	
	Confirm Block Holes1	
00:00:11.16	5: Attach a four-hole block	75.96
	Check Block Alignment	
	Confirm Block Type	
00:00:13.47	6: Attach a flat half-layer block	70.80
	Confirm block height	
	Confirm the block is securely fastened to bottom blocks	
00:00:16.59	7: Attach an eight-hole block	25.36
	Confirm Block Holes2	
00:00:19.74	8: Attach a two-hole block to the far left end	65.16
	Confirm Block Holes4	
	Confirm block is placed in a vertical position	
00:00:23.05	9: Attach a four hole block	25.36
	Confirm Block Holes5	
00:00:24.18	10: Attach a four hole block	25.36
	Confirm Block Holes6	
00:00:25.21	11: Attach a four-hole block with a sloping edge	25.36
	Confirm Block Holes7	
00:00:27.81	12: Use caliper to measure overhang hole	34.35
	Check for all nine parts in the correct location and securely attached	
00:00:28.11	12: Use caliper to measure overhang hole	8.30
00:00:30.81	15: Write dimension on log sheet	12.80
00:00:34.74	13: Place an X on front two joints.	30.08
	Confirm joint location (critical)	
00:00:37.47	13: Place X on back three joints	30.08
	Confirm joint location (critical)1	
00:00:40.47	14: Add stickers, estimate and measure	13.20
00:00:45.77	15: Write dimension on log sheet1	12.80

Task AI Workload Details

IMPRINT Operations Model Report Operator Workload Detail

Analysis Version: Assembly_Task AI

Clock	Task Name	Overall Workload
00:00:00.00	1: Hit lap button on stopwatch to start cycle	4.20
00:00:01.00	2: Pick and Place an eight-hole block	34.56
	Confirm Block Holes	
00:00:02.70	3: Attach a block with four holes	75.96
	Check placement of block to the far right.	
	Confirm Block Holes1	
00:00:05.50	Spec. Orange cannot be matched with blue	219.88
	Spec. Yellow cannot be matched with green1	
	4: Attach a block with four holes1	
	Confirm Block Type	
	Spec. Pink cannot be matched with green	
00:00:09.81	Check Block Alignment	7.60
00:00:10.11	5: Attach a flat half-layer block	75.96
	Confirm block height	
	Spec.: Green blocks cannot stack on yellow	
00:00:14.23	Confirm the block is securely fastened to bottom blocks	6.20
00:00:14.53	6: Attach an eight-hole block	201.28
	Confirm Block Holes2	
	Spec.: Orange cannot stack on blue	
	Spec: Blue cannot stack on green	
	Spec: Orange cannot stack on yellow	
00:00:17.68	7: Attach a two-hole block to the far left end	25.36
	Confirm Block Holes4	
00:00:20.99	Confirm block is placed in a vertical position	7.60
00:00:24.30	8: Attach a four hole block	412.76
	Confirm Block Holes5	
	Spec Pink cannot stack on green	
	Spec Pink cannot stack on red2	
	Spec. Brown cannot stack on yellow	
	Spec.: Brown cannot stack on red	
	Spec.: Green cannot stack on yellow	
00:00:26.43	9: Attach a four hole block	297.60
	Confirm Block Holes6	
	Spec. Brown cannot stack on yellow1	
	Spec. Green cannot stack on yellow	
	Spec. Orange cannot be stacked on blue	
	Spec. Yellow cannot stack on red	
00:00:28.46	10: Attach a four-hole block with a sloping edge	65.16
	Confirm Block Holes7	
	Spec. Orange cannot stack on blue	

Task A Workload Details

IMPRINT Operations Model Report Operator Workload Detail

Analysis Version: Assembly_Task A

Clock	Task Name	Overall Workload
00:00:00.00	1: Hit lap button on stopwatch to start cycle	4.20
00:00:01.00	2: Pick and Place an eight-hole block	34.56
	Confirm Block Holes	
00:00:01.30	2: Pick and Place an eight-hole block	78.90
	4: Attach a block with four holes	
	Confirm Block Holes1	
00:00:02.70	4: Attach a block with four holes	32.26
	Confirm Block Holes1	
00:00:03.10	Check placement of block to the far right.	7.60
00:00:03.40	5: Attach a four-hole block	25.36
	Confirm Block Type	
00:00:05.71	Check Block Alignment	7.60
00:00:06.01	6: Attach a flat half-layer block	32.26
	Confirm block height	
00:00:09.13	Confirm the block is securely fastened to bottom blocks	9.80
00:00:09.43	7: Attach an eight-hole block	25.36
	Confirm Block Holes2	
00:00:12.58	8: Attach a two-hole block to the far left end	25.36
	Confirm Block Holes4	
00:00:15.89	Confirm block is placed in a vertical position	7.60
00:00:16.19	9: Attach a four hole block	25.36
	Confirm Block Holes5	
00:00:17.32	10: Attach a four hole block	25.36
	Confirm Block Holes6	
00:00:18.35	11: Attach a four-hole block with a sloping edge	25.36
	Confirm Block Holes7	

Task ATI Workload Profile

Task AT Workload Profile

Task AI Workload Profile

Task A Workload Profile

APPENDIX F: Subjective Measures

NASA-TLX Questionnaire

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date
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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

Workload Profile Pro-Forma

Workload Dimensions								
Participant #	Stage of Processing		Code of Processing		Input		Outputs	
Task	Perceptual/Central	Response	Spatial	Verbal	Visual	Auditory	Manual	Speech
1								
2								

Instructions:

In each cell on the rating sheet, please provide a number between 0 and 1 to represent the proportion of attentional resources used in a particular dimension for its associated task.

A rating of "0" means that the task placed no demand on the dimension being rated; a rating of "1" means that the task required maximum attention.

APPENDIX G: List of Publications from This Work

1. Bommer, S. C. & Fendley, M. Mental Workload Assessment for Human Systems Design in Manufacturing. *Human Factors: The Journal of the Human Factors and Ergonomics Society* (to be submitted).
2. Bommer, S. C. & Fendley, M. A Theoretical Framework for Evaluating Mental Workload Resources in Human Systems Design for Manufacturing Operations. *International Journal of Industrial Ergonomics (IJIE)* (in review).
3. Bommer, S. C. & Fendley, M. (2015). Reducing Mental Workload Resources in Human Systems Design for Manufacturing Operations. *Proceedings of the 2015 Industrial and Systems Engineering Conference*. Nashville, Tennessee: Institute of Industrial Engineers (IIE).