A Quantitative Analysis about the Impact of Integrating Digital Technology for Formwork Fabrication on Human Factors Perspectives.

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Abstract

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With the current advancements in artificially intelligent machines and robotic systems, the use of digital fabrication tools has become the mainstream of construction industrialization. Digital fabrication facilitates the transformation from design to physical products. Despite the fact that there are several benefits of utilizing digital fabrication in the construction industry, only a few publications have concentrated on how digital technology will increase project productivity, safety, and quality. In detailed, while digital fabrication tools hold promise in reducing worker physical activity, there is a lack of knowledge in the psychophysiological aspects of interaction with these data-driven equipment. This knowledge gap can particularly be realized in the sphere of Computer Numerical Control (CNC) systems, where the worker's mental demand is still unknown. This matter's prominence lies in the potent role of high cognitive workload on human

errors, one of the leading causes of accidents at construction job sites. To bridge this gap, this study aims to investigate three main objectives: (1) to develop and test workflows from design to fabrication processes for formwork production using digital models and CNC machines. These workflows combine VDC trade coordination, 3D parametric modeling, tool path development, and CNC routing in order to produce precision prefabricated formwork components. The productivity of the developed workflows was measured for evaluation purposes. To validate the examined productivity, a case study including prefabricating concrete edge forms for a 25 story post-tensioned, cast-in-place structure has been shown; (2) to quantify workers' mental workload when using CNC machine and to compare this workload with the case when workers fabricate formwork manually; (3) to quantify workers' emotion when interacting with CNC machine and compare this amount with the case when workers fabricate formwork manually. The second and third objectives were obtained by interpreting participants' brainwaves recorded from a wearable electroencephalogram (EEG). To that end, ten subjects having the experience of working with both CNC machine and manual tools were recruited to perform formwork fabrication under two different conditions, operating with and without a CNC machine. Various signal processing techniques (e.g., removing movement artifacts, removing environmental noise etc.) were used to remove EEG artifacts. Then, time and frequency domain analyses were performed to extract different EEG metrics representing workers' cognitive load, such as alpha, beta, and theta power bands. The research team was able to display the difference in mental workload/emotion in the two scenarios using hypothesis testing and different machine learning classifier algorithms. It is expected that the results of this study will provide useful guidelines for contractors to notice the advantages of using CNC machines over that traditional approach and to help them to make better decisions in terms of enhancing their profit margin despite the rising construction-related cost trend.

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DEDICATION

In loving memory of my mom and dad

Chapter 1. INTRODUCTION

With the advancement of technology, industries have started using more automation. It has been estimated that about 50% of all the world's activities have the potential to be automated in the next 20 years (Manyika et al. 2017) . The construction industry is no exception and despite it lags behind other industries in the adoption of digital and "smart" technology (Karji et al. 2017), the construction industry is now increasingly making daily use of these technologies. Bock (2015) asserted there are more than 170 types of robots being developed or tested in various tasks. These tools are mainly designed to perform less desirable and repeatable tasks. There are many known benefits of automation in the industry, including reduction of the time and cost of an activity, quality improvement, and potentially increase in labor productivity. According to Manyika et al. (2017), concerning productivity, the construction industry struggles to keep up with other sectors such as manufacturing and agriculture. Specifically, researchers believed that applying robots and automation could be a solution resulting in performance's improvement in terms of construction productivity. This fact gains more attention in the competitive construction market in these days (Afifi et al. 2016; Ajweh 2014; Zhang et al. 2020). In the same regard, when using automation, the traditional tasks will be replaced by new tasks. The difficulties of these new tasks should be highlighted in terms of physical and mental demands since this factor could inevitably impact the productivity. Overall, on a construction site, 20% to 40% of diverse trade workers consistently exceed commonly established physiological limitations for manual workers (Abdelhamid and Everett 2002). Specifically, measuring mental workload demand in new tasks is critical, as firstly, it could result in errors and productivity reduction, and secondly less attention has been paid to mental demand compared with physical ones. Arya et al(2017) stated that there is a balance between these mental and physical demands, and by reducing one of them, the other one will be increased. Therefore, evaluating the fact that whether automation would shift the extra physical demand to the mental demand is utmost important. Besides the stagnant productivity and slow-changing reputation, the construction industry suffers from labor shortage as well (Liu et al. 2021a). Unstructured and dynamic environment, physically demanding and labor-intensive construction tasks, and unsafe workplaces cause a new generation of workforces to select other occupations than working in the construction fields (Liu et al. 2021a; Manyika et al. 2017). This reluctance can deteriorate the situation in the near future because the aging workforce cannot keep up with the construction demands. Thus, the new potential and automated tasks should be more satisfying for the newly joined construction workers.

In a nutshell and to highlight all the critical aforementioned materials, the ultimate objectives of this research is to measure productivity, mental workload demand, and emotions of workers when using the CNC machine for formwork fabrication. Then, these computed parameters will be compared with the same parameters of the time when workers fabricate formwork in the traditional way (cutting formwork manually). These objectives are extensively underlined in the followings:

1.1 First Objective: Productivity

The empirical AEC research suggests that computational workflows and the use of manufacturing robots or digital fabrication tools extends the opportunities for the digital design and fabrication of building products(Ajweh 2014). These machines help to enhance fabrication productivity as they largely outperform humans in speed and precision of work without posing physiological stress (e.g., fatigue) (Masoud and Samaneh 2012). Furthermore, in term of safety, using CNC machines could support workers to avoid potential occupational hazards such as loud noise, failure of manual equipment, tripping, and getting struck by different machines on job sites.

Despite the potential benefits of using digital fabrication tools in the construction, researchers have highlighted that the construction industry has a low upward rate of adopting and utilizing these machines (Arora et al. 2014; Davidson 2013; Hwang et al. 2018a). This is in part due to the lack of decision-making frameworks, comprehensive digital workflows, transferrable precedents, and shortage of showing all the benefits which could be obtained by using these machines. Therefore, evaluating the fact of whether workers' productivity would improve when integrating these robots for formwork fabrication is of utmost importance. To bridge this gap, the dissertation investigate the common workflows and then proposing a framework with repeatable workflows for the digital fabrication of customized temporary structures and formwork in construction projects. Additionally, this research highlighted and implemented the automation processes that outperform conventional modeling practices in the digital fabrication workflows. Finally, the productivity rate of the suggested framework was evaluated and compared with the previous traditional workflow used in the construction industry(conventional approaches, both on-site off-site. In other words, this dissertation sought to answer the following questions:

- What are the required tasks for both CNC-integrated workflow and the traditional one?
- How could an experienced-based approach of integrating the CNC machine enhance the workflow of concrete formwork between the design phase and the installation phase?
- How can the industry introduce automation into the design phase to the installation phase of concrete formwork using a CNC machine?
- Will the proposed workflow-centered framework improve formwork fabrication productivity?

1.2 SECOND OBJECTIVE: MENTAL WORKLOAD DEMAND

From human robotic interaction standpoint, the integrating of the CNC machine for formwork fabrication requires substantial interactions between humans (operator) and the system (CNC machine). One of the main aspects of human robotic interaction is mental workload demand when working with these robots (e.g. CNC machine) (Liu et al. 2021b). Previous literature has shown that human error and the unsafe behaviors of construction workers are the major cause of accidents in the job-sites (Fang et al. 2016; Garrett and Teizer 2009; Suraji et al. 2001). Fang et al. (2016) further argued that a high mental loading in the tasks could increase the number of errors among personnel in high-risk environments such as the construction industry. In particular, as the majority of the tasks in the construction industry are objective-directed, they require a high capacity of mental function. Therefore, understanding the pivotal role of mental functions in human-error causation is a substantial step in preventing accidents when integrating new automation technologies such as the CNC machine.

To answer the mental workload tasks-related questions, typically, questionnaires have been conducted, which could be distracting and biased. Some of the most popular questionnaire in this regards are: the Cooper-Harper Scale (Cooper and Harper 1969), the Bedford Scale (Roscoe 1987; Roscoe and Ellis 1990) , the SWAT (Subjective Assessment Technique) (Reid and Nygren 1988) and the NASA-TLX (Task Load Index) (Hart and Staveland 1988). This dissertation research deviated from the previous research by using Electroencephalography (EEG) for the cognitive load measurements. As stated by Jebelli et al.(2019a), physiological signals can be used for measuring the human's level of emotions, stress, and cognitive load. Fortunately, with the current advances in wearable biosensors technologies, physiological can be non-intrusively and noninvasively obtained in the field. Physiological measurement variables, especially Electroencephalography

(EEG), can quantify and assess mental workloads by retrieving brainwaves through various channels on the EEG headset.

To address the above gap, the second objective of this research is to evaluate the mental demand of the workers in the formwork fabrication tasks using the CNC machine. Also, the estimated mental workload resulted from tasks using the CNC machine will be compared to the required mental workload when performing the traditional tasks for formwork fabrication. In summary, the paper aims to answer the following questions:

- What would be the required cognitive load of the proposed workflow compared to traditional methods?
- Does using a CNC machine reduce the cognitive load of the workers?

1.3 Third Objective: Emotional State

Since the shortage of workers and their reluctance to work for the construction industry is growing, increasing workers' emotion towards in construction-related tasks is critical. This is imperative, since construction workers' emotional states such as pleasure, displeasure, excitement, and relaxation, could affect their performance in terms of safety, health, and productivity (Hwang et al. 2018b; Jebelli et al. 2018b). In particular, emotions/satisfaction substantially impact the mental process and decision-making abilities of the workers, which might lead to human errors (Bhandari et al. 2016; Easterbrook 1959; Jebelli et al. 2018b; Schwarz 2000). While measuring workers' emotions could bring the mentioned benefits projects, few studies have tried to investigate workers' emotions in the construction domain. Lack of quantitative methods to measure emotions could be one of the main reasons for this remarkable low rate. The Architecture, Engineering, and Construction (AEC) literature demonstrates that most of the previous studies in this regard have followed the psychological surveys and subjective self-assessment, which may suffer from possible bias. Therefore, the objective of this paper is to quantitatively measure construction workers' emotions in formwork fabrication tasks using the CNC machine and then compare that with workers' emotions when performing the fabrication tasks in the traditional approach. Recently, multiple studies have tried to consistently and quantitatively measure human emotions by assessing human physiological responses (e.g., electrodermal activity (EDA), heart rate (HR), blood volume pulse (BVP), and electroencephalogram (EEG)) because an individual's emotions are associated with his/her physiological activities (Chanel et al. 2011; Takahashi 2004). Specifically, using EEG for measuring workers' emotions is preferable as it captures their brain waves from the central nervous system activities (Hwang et al. 2018b). Using EEG could also enable researchers to calculate the valence-arousal-dominance, which represents the emotions (Chanel et al. 2011).

To address the above gap, the third objective of this proposal is to measure construction workers' emotions in formwork fabrication tasks using the CNC machine and then compare that with workers' emotion when performing the fabrication tasks in the traditional approach/manual approach. This could assist researchers in showing that integrating robotics and digital fabrication tools will facilitate construction workers instead of replacing them. To sum up, the objective of this study aims at answering the following questions:

- What would be the demands of the required tasks of the proposed workflow compared to traditional methods?
- Does using a CNC machine increase the satisfaction of the workers?

Chapter 2. LITERATURE REVIEW

2.1 DIGITAL FABRICATION

As the construction industry moves toward using advanced technology, digital fabrication has emerged as an essential approach for improving productivity and quality. Seely (2004) defined digital fabrication as a computer-aided procedure to alter component material output with the addition or subtraction of layers. Digital fabrication is known to have the following two benefits: (1) The designed shapes and connections which were previously impossible to build because of labor, time, and cost limitations, are now made feasible through the efficiency of digital design and fabrication;(2) Conventional building and design techniques can also be translated in digital production terms enabling the contractors to obtain an economically practicable construction process (Hanlon 2017). The Massachusetts Institute of Technology (MIT) first used digital fabrication in the 1950s to manufacture complicated aircraft parts with a numerically controlled milling machine (Gershenfeld 2012). Since 1990, digital fabrication from digital data to physical objects captured significant attention in the AEC industry,

There are several digital fabrication tools (i.e., robots) mainly used in the AEC industry, such as 3 dimensional (3D) printers, 3-, 4-, or 5-axis CNC routers, laser cutters, plasma cutters, and water jets. Choosing the most appropriate tool for the given task or material and its related procedure is key to getting the desired outcome in the digital fabrication field (Congdon, 2014). By and large, the most common process used in these robots is subtractive or additive fabrication (Naboni and Paoletti 2015).

- **Additive**: Additive fabrication, also known as rapid prototyping, is a fabrication process that includes layering materials into the desired shape. 3D printing, layered stereo lithography (SLA), and solid freeform modeling are some of the digital fabrication tools falling under the category of additive manufacturing. Additive fabrication supports varying levels of detail depending on the thickness of these layers. For example, highly complex, zero tolerance and exact shapes can be generated with additive fabrcation (Krauel et al. 2010; Naboni and Paoletti 2015).

- **Subtractive**: In subtractive fabrication, materials will be taken out volumetrically by drill-bit movement. In other words, it removes material from the original shape to achieve the desired design. This removal can be carried out either chemically (e.g., etching), or mechanically with a milling machine (Congdon 2014). For milling, two and a half to three-axis mills, or even five-axis types of milling machines, are mainly adopted in the AEC industry. The number of axes indicates the machine's movement during cutting. For example, a three-axis mill can cut in any direction laterally, as well as up and down (Congdon 2014).
- **Formative:** Formative fabrication includes applying mechanical forces, restricting form, heat, and steam to shape the material into a favorable Figure. In this deformation process, there might be some axially or surface bounds(Congdon 2014).

CNC machines are digital fabrication robots mainly categorized in the subtractive fabrication. The following section highlight the benefit of CNC machines in the AEC industry.

2.2 BENEFITS OF CNC MACHINE

Finding the most optimal procedure for design to fabrication of formwork using a CNC machine requires a good understanding of the capabilities and the benefits that the machine can offer. Masoud and Samaneh (2012) compared the activities using CNC machines and manual machines in a part of a study. They indicated that using CNC machines might remove several manual tasks in cuttings such as: obtaining and studying the drawings, selecting the most suitable machining methods, deciding on the setup methods, selecting the cutting tools, establishing feed and speed for each tool, machining the parts. They added that on manual machines, there is a need to set up each of them before using as well as moving them during the cuts while holding them. This body motion will be repeated for each part of the batch. Albert (2011) argued that working in a high-level performance might be infeasible in the construction industry for a long time. Particularly, in fabricating formwork, keeping the dimensional tolerances and high-quality finishes is challenging when working with manual machines. In a nutshell, Masoud and Samaneh (2012) reported that adopting a CNC machine provides the following benefits to projects: (1) reduction in setup time, (2) reduction in lead time, (3) accuracy and repeatability, (4), contouring of complex shapes, (5) simplified tooling and work holding, (6) consistent cutting durations, and (7) increased productivity. In this regard, Keller et al. (1982) stated that applying CNC machines could increase the productivity rate by 3 to 4 times than manually operated machinery. Less complex manufacturing systems for different design scenarios (Tepavčević et al. 2017); panels for different building components such as walls, floors, roof, and stairs (Altaf et al. 2018); rapid manufacturing in the early design of an architectural idea to validate the feasibility of design criteria(Lee 2016; Pignataro et al. 2014); CNC machine rebar manufacturing (Navon et al. 1995); CNC milled formwork (Jewett and Carstensen 2019); and custom or free-form designed molds and panels (Jovanović et al. 2017; Lee 2016) are some of the services supported by CNC machines in the construction industry resulting in productivity improvement.

From the human factors standpoint, Dozzi and AbouRizk, (1993) suggest that factors such as fatigue, motivation, physical limitation, and safety could make it infeasible for a construction worker to maintain a high-level performance for a long time. Therefore, the industry values the tools that address these human-factors and mitigate the issues associated with the manual processes. From the safety point of view, traditional formwork production activities such as lifting, sawing, and hammering by carpenters can result in frequent though low-severe injuries (Fardhosseini et al. 2015; Pratama et al. 2018). Also, prolonged awkward postures, and high physical workload in conjunction with the frequent use of hand tools are ergonomic hazards that can reduce workers' productivity and increase lost-time costs (Aghazadeh and Mital 1987). Therefore, not only can innovations in formwork fabrication help workers avoid occupational hazards, they can also save design and production costs for contractors and promote consistent and high-quality formwork cuts (Spielholz et al. 1998).

2.3 Design to Fabrication Workflows

Design to fabrication refers to the automation procedure of eliciting and processing the model's information and then transforming them into operational instruction of digital fabrication tools such as CNC machines (Raspall 2015). This data transfer between design and the machine could lead to more controllability over the allocated tasks, eventually resulting in less rework (Hamid et al. 2018). Automating the design process in prefabrication workflows can provide a significant time/cost advantage to the production processes(Manrique et al. 2015). To implement this, in the first step, practitioners usually use Computer-Aided Design (CAD) tools to design and analyze products' geometry. CAD is a generally adopted platform to design and to analyze the object's geometry, which is typically the first step of any design-to-fabrication workflow(Hamid et al. 2018). Then, a Computer-Aided Manufacturing (CAM) tool will be used to convert the cutting procedure into instructions (Fardhosseini et al. 2019, 2020; Hamid et al. 2018). In brief, CAD/CAM procedures entail the use of technologies for design, analysis, and manufacturing of products (Fardhosseini et al. 2019, 2020; Hamid et al. 2018; Schodek 2005). In the final step of the design to fabrication workflows, a manufacturing robot, like a CNC machine, is needed to convert the instructions generated in CAM to machine operational tasks. The CNC machines work based on a controller application providing the machine-code (G-code). This code instructs the machine to operate based on the CAM outcome (Hamid et al. 2018).

Considering these main steps, many authors have suggested a design-to-fabrication workflow. The AEC literature has shown that although design-to-fabrication workflows are being developed in commercial construction, there are still manual processes in the digital workflows that may offer automation opportunities. Two recent studies, Arashpour et al. (2018) and Hamid et al.(2018), presented workflows for fabricating commercial façades (using additive manufacturing) and for wood cabinets engineered to order, respectively. These studies confirmed that despite considerable investment needed for these machines, the industry could obtain a positive return on them if the workflows are used recurrently across multiple projects for customized building(Arashpour et al. 2018; Hamid et al. 2018). They added that developing an automated workflow could greatly assist the construction industry. In another study, Hardin (2015) highlighted the framework by American Building Innovation (ABI) in which wood-framed walls resulted from a link between Building Information Modeling (BIM) and CNC machines. However, that paper did not clarify the details behind the commercial implementation of the suggested workflow. In the same vein, Schüco (2016) proposed a plugin for complicated glazed façades that are based on the method used for curtain walls. Although they uploaded their plugin online, the source is limited to promotional material by the company itself. In this research, the authors aim to catalyze the previous studies and propose a framework with repeatable workflows for the digital fabrication of customized temporary structures and formwork in construction projects.

2.4 DIGITAL FABRICATION AND PRODUCTIVITY

The term "construction productivity" relates to how good, how easily, and at what expense buildings and facilities can be constructed (Council et al. 2009). While productivity is a significant metric, the construction industry lacks a standard or official productivity index, which creates some uncertainty when comparing different values (Shehata and El-Gohary 2011). However, The common opinion overall is that productivity usually means the generated output for a specified quantity of input (Dozzi and AbouRizk 1993, 1995).

Numerous research have been conducted on the productivity of building robots and digital fabrication. For example, in a comprehensive study, Lloret et al. (2015) shed light on how technological and industrial advances have empowered architects, engineers, and contractors to build intricate architectural formwork concrete. Their study first overviewed static formwork systems and suggested methods to improve its adaptability toward intricate forming concrete by integrating digital fabrication into conventional casting procedures. In a static formwork system, the formwork is typically fabricated by "milling" a foam or wood component into forms with a CNC machine. This strategy enables the contractor to customize and build any kind that they need. Although milling in this approach requires high cost and electricity consumption energy, it is still known as the most efficient method for casting complex formworks (Lloret et al. 2015; Lloret Kristensen 2013). Skibniewski and Hendrickson (1988) explored the risks and advantages of using robots for on-site surface finishing works, and confirmed that in a technological and economic standpoint, the usage of robotics for routine surface application activities is feasible. In another study, Balaguer et al.(1995) addressed many facets of the robotics manufacturing of GRC panels in economic, quality and technical terms, based on actual performance rate calculations and real-world cost estimates, and underscored the productivity benefits of these robotized spraying panels over manual manufacturing. Castro-Lacouture et al. (2007) investigated the potential productivity gains from automating concrete paving operations and discovered that the generated automated process could improve productivity considerably. Warszawski and Rosenfeld (1994) examined at the feasibility of multipurpose robotics performing interior construction activities. This research measured the time and costs of robotized and manual construction to show the potential for increased productivity of robotic construction. In a similar study, Garcia de Soto et al.(2018) evaluated the cost and time required to build a robotically-fabricated complex concrete wall onsite to determine the impact of digital fabrication on productivity. They demonstrated that when the robotic construction system is used for complex walls, productivity increases, meaning that using additive digital fabrication to set up complex structures would provide major economic benefits.

From one side, previous research showed that, in buildings with concrete structures, the cost of concrete formwork can constitute up to 60 percent of the cost of all concrete work-packages in projects (Hardin and McCool 2015). Given the significance of this cost, value-adding innovations in the design planning, and particularly productivity of concrete formwork can benefit the projects. Form another side, digital fabrication approach can boost building industry’s productivity not just because they save time on complicated tasks, but also because they can pass design data directly to 1:1 assembly processes and automated development(Keating and Oxman 2013). Therefore, as mentioned above, the first objective of this dissertation is to present automated workflow of using CNC machine for formwork fabrication, and then evaluate the productivity of this approach vs the traditional one.

2.5 Mental Workload

CNC machines are digital fabrication robots mainly categorized in the subtractive fabrication. The following section highlight the benefit of CNC machines in the AEC industry.

When adopting a novel approach in construction projects, such as using a CNC machine for formwork fabrication, analyzing the mental workload in the tasks becomes crucial as sometimes the innovative tasks demand higher mental skills of workers. For example, Howell and Cooke (1989) believed that the integration of new technology has increased, rather than lowering the mental workload demands. In particular, repeatable and predictable tasks are performed by machines, whereas operators are accountable for tasks containing inference, diagnoses, judgment, and decision making (Militello and Hutton 1998). Therefore, operators working with robotics such as CNC machine may need to gain an understanding of what a robotic supported construction project looks like, what new knowledge is required, and to what role that knowledge is attributed to ensure effective interaction between the robotic system and the wider construction project, to what extent is the operator involved? How complex is the task? Is the operator able to perform additional tasks at the same time as the main one? Is s/he able to respond to any particular stimuli? How is the operator feeling at the time of performing his/her tasks? (Dowsett et al. 2018; Rubio et al. 2004). Therefore, measuring the mental workload of construction workers when using CNC machines for formwork fabrication is of utmost importance.

The concept of mental workload or cognitive workload refers to the overall amount of human mental effort or memory required for the execution of a task (Sweller 1988). In detail, Baddeley (1992) defined mental workload as "a brain system that provides temporary storage and manipulation of the information necessary for such complex mental tasks as language comprehension, learning, and reasoning." The capacity of mental workload for information storage and coordination of resources to conduct an activity at the same time is limited, which prevents people from beaning multitasking (Baddeley 1992). Therefore, activities requiring a high demand for mental resources might lead to insufficient capacity to maintain an acceptable performance level. On the other hand, activities requiring a low demand for mental resources might lack the focus and diligence needed to complete a task appropriately (Hart and Staveland 1988; Mitropoulos and Memarian 2012).

In the construction industry, the lack of working memory adversely impacts the workers' risk perception and may lead to in-attentional blindness (Chen et al. 2016a). In-attentional blindness is a psychological phenomenon where an individual fails to identify stimuli due to this lack of attention. When a task demands too much mental load, the workers tend to be exposed to a higher error rate and vulnerability because of insufficient working memory (Chen et al. 2016a).On the other hand, when a task is repetitive and requires a relatively low mental load, workers find the work tedious, resulting in more insufficient focus and more deficient diligence (Schnotz and Kürschner 2007). Both of the above cases could cause mental fatigue. Mental fatigue leads to effort disinclination, reduction in efficiency and alertness, and impaired mental performance(Zhao et al. 2011). In summary, considering workers' mental fatigue is critical as it results in a lack of focus and diligence in performing tasks appropriately (Mitropoulos and Memarian 2012), detecting hazardous signals (Newnam et al. 2006), and learning from training (Lorist et al. 2000). Therefore, a reliable and quantitative assessment of physiological and mental workload is the key to meaningful and proper task allocation. The current mental load assessment approaches can be divided into three categories: physiologic, secondary task, and subjective measures (Carswell et al. 2010; Dadi et al. 2014). Physiologic measures quantify mental load through its indirect reflection in physiological information, such as cardiac response (Carswell et al. 2010). Secondary task measures use workload capacity to represent work quantity (Knowles 1963). Subjective measurement requires the test subject to self-report their feelings after performing the task (Dadi et al. 2014). In this research, we are going to use an electroencephalogram (EEG) to measure the workers 'mental workload when using a CNC machine and compare it with the demanded mental workload in the traditional approach.

2.6 ELECTROENCEPHALOGRAM (EEG)

An electroencephalogram (EEG) is an alternating type of electrical activity recorded from the scalp surface (Schomer and Silva 2012). Typically, measuring EEG is based on two primary techniques. In the first approach, the EEG is directly measured via the voltage fluctuations created by neurons at the scalp (Khalil and Misulis 2006; Sanei and Chambers 2013). In the second type, EEG is measured via a depth probe inserted directly into the brain tissue (Jebelli et al. 2018a, 2019a). The EEG electrodes' location on the scalp's surface plays a vital role in obtaining information (Koessler et al. 2007). Precisely, the cerebral cortex and its regions, such as the frontal lobes, motor cortex, and parietal lobe, determine different functions(Teplan 2002). For example, the frontal lobe specifies tasks related to emotions and attentions (Rusinov 2012), while the motor cortex determines voluntary movements related tasks and thereby could be used to monitor brain activation from physical movements (Rusinov 2012). Previous studies have explained EEG in terms of rhythmic activity classifying it into the main following five categories according to frequency bands(Borghini et al. 2014; Jasper and Andrews 1938; Walter and Dovey 1944).

- delta (0.5–4 Hz)
- theta (4–8 Hz)
- alpha (8–13 Hz)
- beta (13–30 Hz), and
- gamma (>30 Hz)

The delta and theta frequency ranges are usually observed in infants, children, and sleeping adults — the alpha frequency range bands conscious thinking and the subconscious mind, promoting a feeling of deep relaxation. The beta frequency range is the usual walking rhythm of the brain associated with active thinking and attention; it clearly shows brain activation during motor cortex activity(McFarland et al. 2000; Pfurtscheller and Lopes da Silva 1999). The gamma frequency range has a very low amplitude and thus is rare in normal adults. It is usually observed in clinical domains and used to detect certain brain diseases.

Several studies in the AEC literature report the substantial correlation between EEG brain rhythms and mental workload (Pfurtscheller and Neuper 1997; Sterman et al. 1994). EEG could support researchers to gain a multidimensional received signal, which can handle many complicated signal processing studies and research directions, such as data fusion, machine learning, and pattern recognition (Cohen 2014; Zhang et al. 2019). Therefore, EEG is the best candidate for direct observation of the mental workload of construction workers.

Figure 2.1. Lobes of the Cerebral Cortex, EEG headset, and the location of the electrodes.

2.7 Construction Workers' Emotion

Research in construction relating to robotics has so far concentrated on how mainly to deploy a robotic device shops, construction environments, and construction sites to assist workers with facilitating conventional construction tasks. However, as the enhancement of using robotics into construction moves forward from principle to practice, all aspects of robotic implication, including the operators' emotion, should be taken into considerations (Dowsett et al. 2018). Understanding construction workers' emotions at the workplace is highly crucial since workers' emotions is connected with many organizational performances. In particular, emotions have a huge impact on the cognitive process and decision-making abilities (Bhandari et al. 2016; Easterbrook 1959; Schwarz 2000). For instance, workers' perception of the current condition could be affected by high arousal, which can even lead to variation in workers 'subsequent behavior (Easterbrook 1959). This influence on workers' perception could also result in failing in hazard identification, which can directly threaten workers' safety. In addition, workers' emotions could impact whether the decision processing is heuristic (i.e., high reliance on pre-existing knowledge structures) or systematic (i.e., analytic and cognitive processing with close attention to the relevant information in the present situation). This change in the type of decision process could affect the outcome of decision making (Kruglanski and Higgins 2013; Schwarz 2000). Heuristic decision processing is mainly based on emotions (e.g., low fear of skilled workers who are accustomed to dangerous work conditions) could lead to unsafe and unproductive behaviors. That is one of the major reasons why the interpretation of the effect of worker' emotions on decision-making is vital in construction, where a worker is continuously engaged in making a series of task-related improvised decisions (Hwang et al. 2018b; Jebelli et al. 2017). According to Ashforth and Humphrey (1995), classifying emotions into categories is complex, overall, individuals' responses to an external stimuli or event essentially describe their emotions (Eysenck and Keane 2005; Lazarus 1982). As a result, it could be stated that emotions can be measured based on the resources of individuals' ability to cope with the situation. Therefore, measuring the workers' emotion when using the CNC machine is substantially valuable.

One of the acceptable approaches to measuring emotions is to classify them from a dimensional perspective based on the valence-arousal-dominance (VAD) model (i.e., a valence dimension from displeasure to pleasure, an arousal dimension from not aroused to an excited state, and a dominance dimension from being in control to a feeling of being controlled by the emotions) (Mehrabian 1996). Valence, varying from negative to positive, and arousal, varying from low to high (Anders et al. 2004; Baumeister et al. 2007)

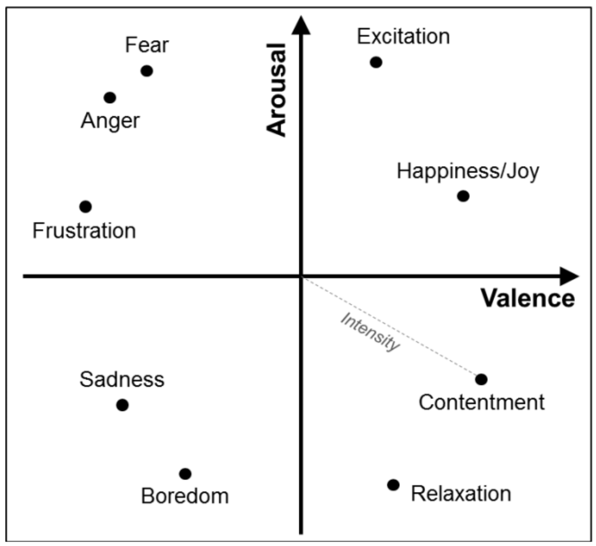


Figure 2.2. Valence-Arousal Model and Emotion (adopted from Hwang et al 2018).

Given that a construction workplace has many changing emotional contexts (i.e., emotions-related stimuli such as different work conditions and tiredness over time) that workers experience every day while significantly affecting their work performances (Allcorn 1994; Bensimon 1997), understanding emotions in the workplace provides meaningful insights for enhancing work performance. To do this, continuous and quantitative emotional state measurement in the field is necessary, which is what this study aims to achieve.

Chapter 3. RESEARCH METHOD

The objectives of this study are (1) to first investigate the common workflows for design to installation, proposing an automated workflow using CNC machine, and then evaluating the productivity of all suggested workflow; (2) to evaluate the mental demand of the workers in the formwork fabrication tasks using the CNC machine; (3) to measure construction workers' emotions in formwork fabrication tasks using the CNC machine and then compare that with workers' emotion when performing the fabrication tasks in the traditional approach. To achieve the above objectives, two main steps (workflow and productivity; experimental research) were taken which will be described as follows:

3.1 WORKFLOWS AND PRODUCTIVITY

In the first step of research method, researchers just focused on developing an automated workflow from the design to the installation phase of formwork using digital models and CNC machines. The objective was achieved through an applied research project with a large General Contractor (GC), Turner Construction Company (Turner). Turner formed a research and development team of BIM/VDC professional, university researchers, and digital design programmers. The team first observed and documented the traditional processes for designing and fabricating concrete formwork in several in-progress projects both at the jobsite and at the prefabrication shop (for those projects that the formwork was prefabricated manually). In this regard, the team used a task analysis approach to both classifying and simplifying the observed processes into standardized, reproducible stages in projects with elevated concrete slabs. This workflow focused on the design, fabrication, and installation of edge formwork for elevated concrete slabs. Then, the same workflow and task analysis techniques were carried out for the scenario of using a CNC machine for formwork fabrication.

To better understand the tasks for design, fabrication, and installation and how the new workflow could replace the traditional one, researchers conducted 6 interviews with skilled and experienced practitioners such as carpenters, CNC operators, concrete experts, Virtual Design Construction (VDC) employees, and finally, superintendents. These experts were selected for their expertise and professional experience in each workflow and could bring up issues that the research team potentially overlooked. For this study, 13 experts were contacted, of which 6 accepted the invitation to participate in the interview (a 46% response rate). Four open-ended questions were designed to gain expert opinion about different workflows, tasks, gaps, and potential improvements in each workflow regarding the interview protocol. People who responded had an average of about ten years of experience in the mentioned fields.

These interviews help the researchers to identify common tasks and outline different workflows for cutting slab formwork in the projects (manually cutting at the jobsite, manually cutting in prefabrication shop, cutting using the CNC machine). Required tasks for manually cutting at the jobsite and cutting slab formwork in the prefabrication shop were highlighted in the research team observations and validated based on the interviews. In summary, the interviews help the researcher to verify and modify some parts of the suggested task analysis. Then, the research team outlined workflows based on each of these approaches so that the main different tasks in these workflows can be compared with the workflow using the CNC machine. Following are the main criteria for developing workflows: (1) Creating a digital model of the project (the GC's perspective); (2) Trade coordination and constructability review; (3) Drafting Post- Tension (PT) strands/embeds and coordinating the constraints (e.g., location of PT holes); (4) Establishing formwork design requirements and constraints (e.g., materials, maximum allowable size, clearance for avoiding formwork cuts near PT holes); (5) Designing, drafting, and labeling each component of formwork per location and constraints; (6) Cutting formwork components with manual carpentry tools.

In the initial development of the CNC machine workflow, the team attempted to take advantage of the coordination model to facilitate the target formwork's digital design and fabrication. The team chose interoperable and customizable software (customization through the Application Programming Interface – API) that could support modeling, review, coordination, drafting, and fabrication of formwork in all projects. With the flexibility to choose any model-authoring tool, the team chose Autodesk Navisworks as a universal model reader for project review, clash detection, and coordination. For creating PT elements and modeling formwork in 3D, the team used Rhino with Grasshopper as a parametric modeling tool that could work with the variation of parameters/constraints across different projects. Finally, for a seamless data transfer from the model to a CNC machine, the team used Rhino-CAM, translating the model into cutting instructions for the machine. After the successful implementation of the first development, the team aimed for automating manual modeling processes and manual checks in the model (e.g., checking if a proposed cut intersects with PT, embeds, or PT holes, labeling formwork, extracting 2D views, placing them on installation sheets and optimally cutting plywood to get minimum waste). The team used visual programming in addition to API functionalities (Rhino/Grasshopper API using Python language and algorithms) to automate many of the manual modeling tasks/checks.

After incrementally refining the workflow in a series of field tests, the team was able to fully implement, validate, and evaluate the CNC automated workflow. The next step was to compare the developed workflow with the other manual-based ones in terms of productivity. As the GC self-performs all concrete work in its portfolio of projects, the team had direct involvement in fully implementing the project's workflow. To evaluate productivity, the timing of all the tasks in the different workflows were recorded for a floor. The productivity rate for each floor is defined as (Schwartzkopf 1995):

$$P= T/A \tag{3.1}$$

P represents productivity rate, T shows the timing for all the tasks from the design phase to the installation phase, and A demonstrates the floor's net area so that we can normalize the rate. This rate will be compared with the two previous conventional workflows. The productivity rates and the timing to complete each task in all workflows are recorded by the GC and available to the researchers. The research team used a case study to assess productivity differences between manually fabricated and digitally fabricated edge formwork. The team collected productivity data (timing data) for three floors of a 26-story commercial building project located in the Pacific Northwest region of the U.S. In detailed, the team collected the required timing for the tasks in the three workflows (traditional, prefabrication without CNC machine and prefabrication using CNC machine) for three floors of the building. After collecting the time for each workflow, the research team verified that with the workers who were involved in that tasks, and asked them to give pessimistic, optimistic, and most likely timing for completing these tasks. These workers were a VDC project manager, a VDC project engineer, a skilled worker, a laborer, a CNC operator, and a carpenter who were performing tasks in any of the three workflow. For the final validation, all of these data were again validated with the carpenter’s superintendent for manual –related tasks on the jobsite and prefabrication shop, and with the VDC project manager for the CNC machine related ones. Therefore, by conducting a time study for the suggested workflow using digital models and CNC machines, the researchers were able to show the potential enhancement in productivity of using the proposed workflow for concrete formwork. Figure 3.1 represents the framework that the research team followed in conducting this research.

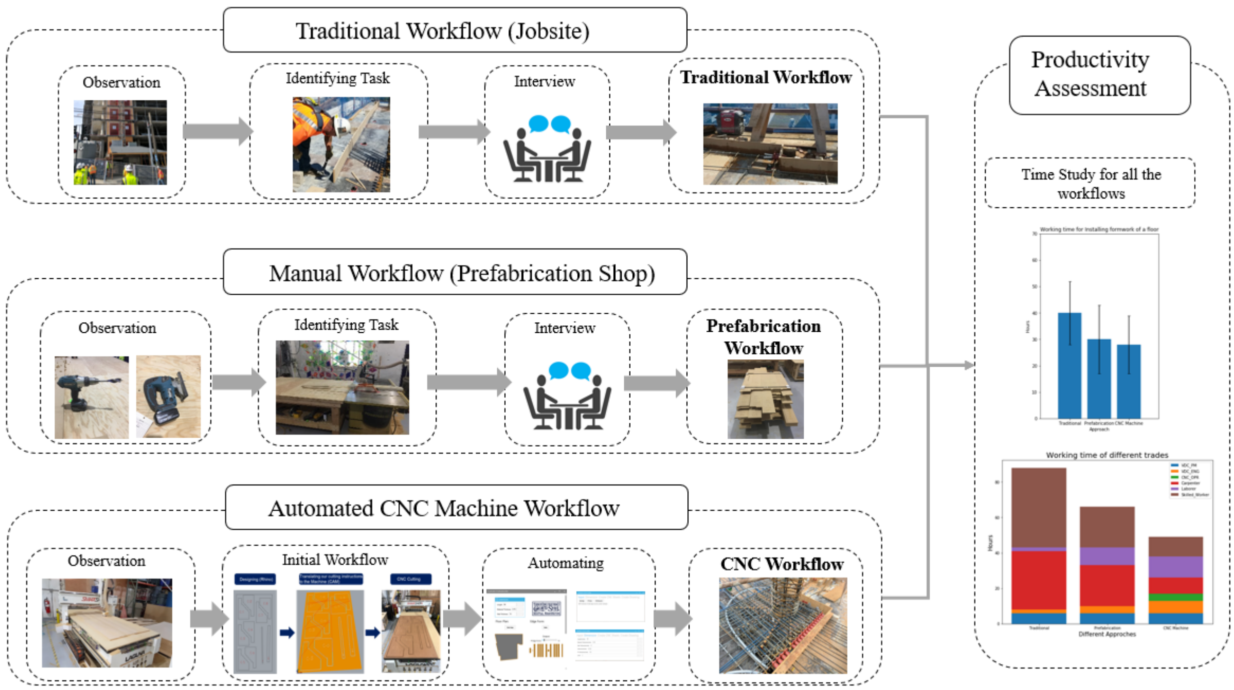


Figure 3.1. The framework of the research method

Despite the evaluation of the three workflows in terms of productivity, the research team just focused on prefabricated manually as well as CNC machine workflows for measuring mental workload/emotion of the workers. This will allow the team to disregard potential artificial signals such as noises in the jobsites and enable them to just compare mental workload/emotion.

3.2 Experimental Research for Mental Workload and Emotion

In order to achieve the second and third objective of this dissertation, an experiment was conducted. Researchers recruited 10 subjects who had expertise in both digitally (using CNC machine) and manually fabricating formwork while wearing the EEG headset. Then, based on the collected data the subjects' mental workload/emotion was evaluated in the two approaches (Fabricating formwork using CNC machine and manually fabricating formwork). Below is the details of the research we used:

3.2.1 *Data Collection*

The main objective of this part of research is to compare construction workers' mental workload demands/emotion in the following two approaches: (1) fabricating formwork using a CNC machine; (2) traditionally fabricating formwork (cutting manually). To remove additional mental workload/emotion noise from external environmental conditions, the experiment for both approaches was conducted in the prefabrication shop in a controlled environment. Subjects were asked to perform three tasks from the CNC cutting approach including tool path development, sourcing materials, and CNC cutting and three tasks from the traditional approach included finding the piece's dimension, cutting the piece using a table saw, drilling the post-tension holes and cutting notches while wearing an EEG headset. The key tasks were defined in Table 3.1, and the corresponding workflow for each approach was presented in Figure 3.2. As shown in Figure 3.2, modeling and installation on the job site tasks are similar in the two approaches. Therefore, the research team focuses on comparing the required mental demand/workers' emotion in the three other tasks. As the modeling part is identical, the research team designed a piece of formwork for the experimental task activities.

Subjects were asked to use an EEG headset during the experiment. Emotiv EPOC+ is an inexpensive off-shelf EEG wireless headset providing EEG signals with a decent quality(Badcock et al. 2013; Vokorokos et al. 2012). Emotiv EPOC+ was connected via a USB transceiver wirelessly to a nearby laptop during the experiment. Sequential sampling data were captured internally at 2,048 Hz and a deliverable rate of 128 Hz. With connectivity in a 2.4 GHz-band, and a dynamic range 8.400 μV (pp), the data collection resolution was set at 14 bits. Also, the felt pads used by the Emotiv EEG system were wetted with a solution suggested by the manufacturer to strengthen the contacts between the electrodes and participants ' scalps.

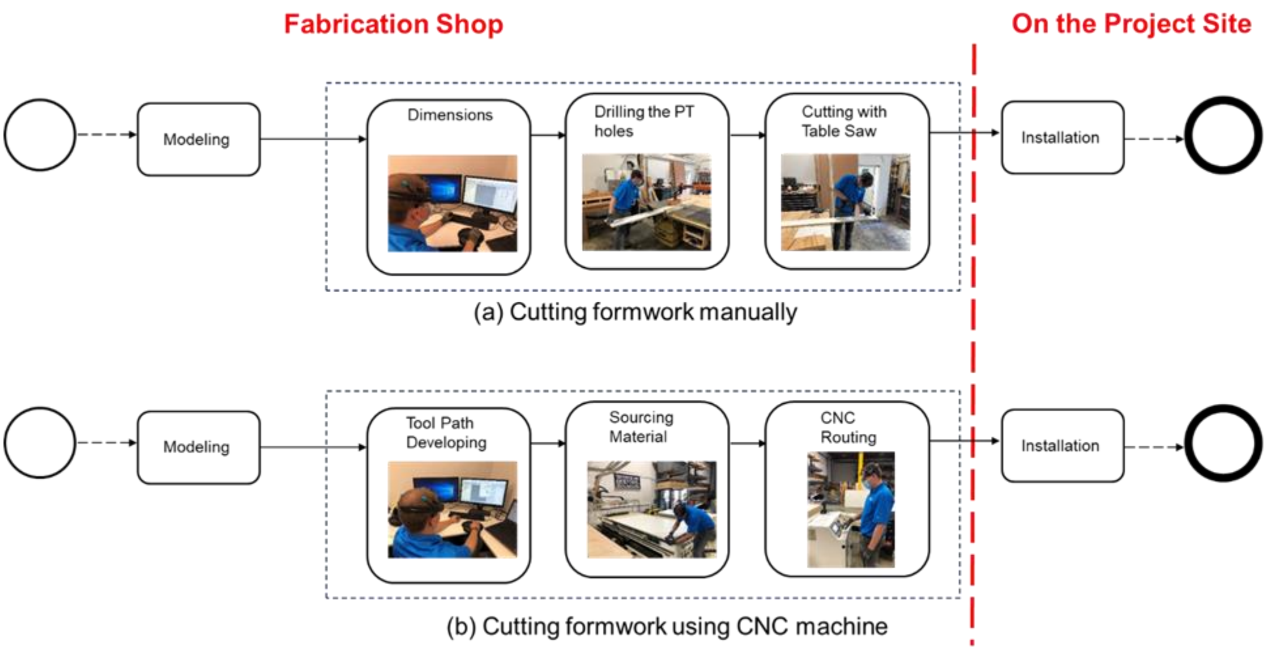


Figure 3.2. Tasks for formwork fabrication in the traditional way (a) and when using the CNC machine (b).

Table 3.1. Definition of the tasks performed for formwork fabrication in the traditional approach and when using the CNC machine.

	Traditional Approach
Task	**Definition**
Dimension	Highlighting all the needed dimensions of the formwork piece to cut it manually(Using Rhino)
Cutting using Table Saw	Cutting the piece into the appropriate with using the table saw.
Drilling the PT Holes	Drilling the post-tensioned holes as well as cutting the piece into the found length. Finally, cutting out the notch designed in the formwork piece
	CNC Machine
Task	**Definition**
Tool Path Developing	Using Rhino cam to translate cutting instruction for the CNC machine (Choosing an appropriate bit, adopting smooth feed rate and spindle speed, determining the cut depth, etc.)
Sourcing Material	Lifting the plywood on the CNC bed and aligning that with the CNC edges based on the defined origin

CNC Routing	Choosing the developed file in the tool pathing step and run it on the CNC machine

The three considered tasks in the traditional approach were: dimensions, cutting using the table saw, and drilling. In the dimensioning task, subjects were supposed to find the dimensions of the designed formwork piece. The research team asked the subjects to use Rhino to find out any dimensions needed for cutting the piece manually. After this task, a corrected dimension drawing sheet measured by the research team was given to participants. In the second task of the traditional approach, participants were supposed to cut a plywood sheet based on the piece's width shown in the drawing sheet. To this end, they should have set the table saw based on the given dimension and cut a plywood piece to obtain the piece with the desired width. Finally, in the traditional approach's last task, the subjects were asked to drill the Post-Tension (P.T.) holes and cut out the notches based on the given drawing sheet. A drilling tool, tape measure, marker, and a sawing tool were provided for them. They were asked to use the tape measure to find the P.T. holes spots and the designed notch. They were then supposed to use the drilling tool to drill out the holes first and then the sawing tool to cut out the notch. The last part of this task was to cut the piece length based on the obtained drawing sheet using the sawing tool (Figure 3.3).

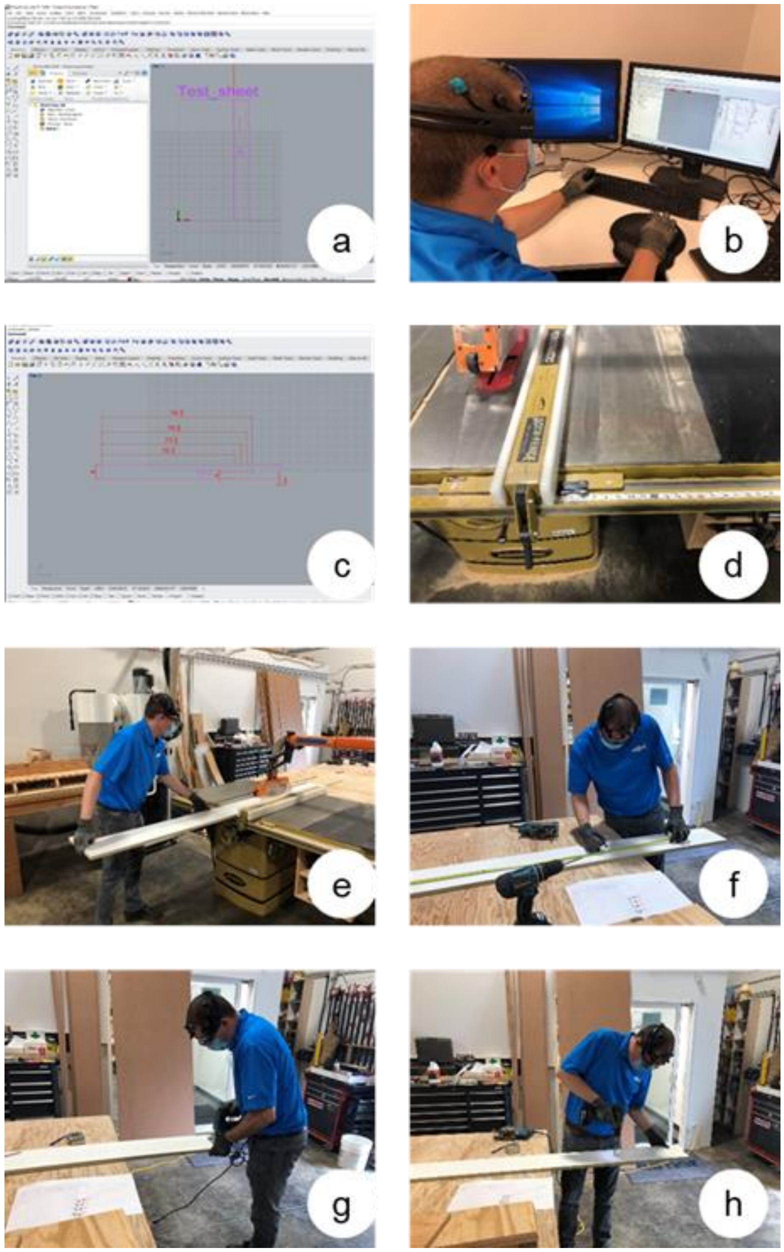


Figure 3.3. Tasks performed by the participants to cut formwork manually (traditional approach): (a) the given formwork model to the participants;(b) Finding out the required dimensions;(c) Giving the participants the correct drawing sheet, including the dimensions so that they can cut the rest of the formwork based on that;(d) Setting up the table saw; (e) Cutting the piece into the desired width;(f) Finding the P.T. holes' spots and the notch; (g) Cutting the notch;(h) Drilling the P.T. holes.

Using the CNC machine for formwork fabrication, tasks such as tool path development, sourcing materials, and CNC routing were considered in the new approach. Similar to the traditional approach, the model was given to the participants, and they were asked to use Rhino CAM to develop the G-code. In other words, the CNC machine works based on a controller application providing the machine-code (G-code). This code instructs the machine to operate based on the CAM outcome. As a result, based on the material and the CNC machine's characteristics, the subject had to determine the cutting bit with the appropriate feed rate and spindle speeds. These critical variables can influence the service life of CNC machines. In addition, they considered vital variables in CNC cutting, such as the cutting depth, cutting type (profiling, pocketing, V-carving, and roughing), and the cut directions (down cut, up cut, or mixed). Finally, subjects had to generate the G-code based on all of these decisions they made. Next, subjects were asked to lift plywood and put it on the CNC machine bed to align their edges (sourcing material). This is imperative as misalignment of the plywood and the CNC machine bed could affect the cutting procedure. In this approach's last task, subjects were supposed to upload the generated G-code in the CNC machine and run it to fabricate the designed formwork (Figure 3.4).

Since the subjects' mental activity may be impacted with each task performance, all the subjects have been randomly assigned to perform the two approaches so that half of the subjects start with the CNC machine-related tasks first and the other half begin with the manually cutting related tasks. This allows the researchers to detect potential bias, which could have been caused due to the order effects.

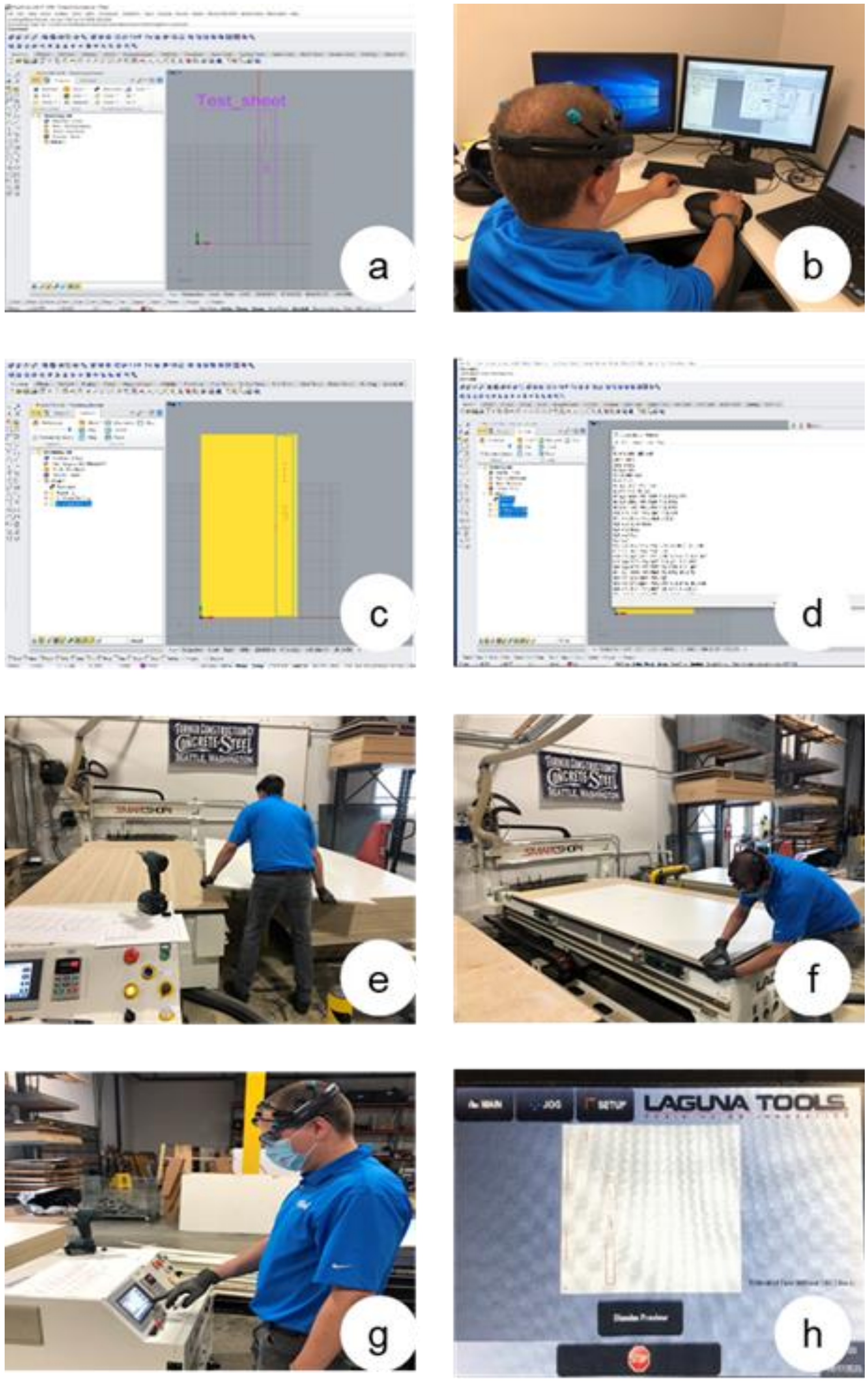


Figure 3.4. Tasks performed by the participants to cut formwork using CNC machine: (a) the given formwork model to the participants;(b) Using RhinoCam to determine cutting variables;(c) Simulate the result of the RhinoCam;(d) Developing G-code; (e) Lifting plywood(sourcing material);(f) Aligning the plywood with the CNC bed;(g) Working with the CNC machine to run it; (h) Final review before running the CNC machine.

3.2.2 *Subjects*

The research team recruited ten healthy, non-disabled adults to participate in this experiment (IRB approval number: UW STUDY00009559). All subjects had the experience of working with the CNC machine as well as working in the field of carpentry. In addition, they all signed a consent form that described all the experimental procedures prior to their participation. They were also asked whether they had any physical or physiological issues (e.g., headaches, quick breathing, feeling dizzy, and feeling fatigued), cognitive (e.g., focus trouble and poor sleep quality), and emotional problems (e.g., feeling sad, helpless, and cynical). None of them mentioned any of such issues. The authors also told each participant that if they feel uncomfortable in any experiment stage, they could stop the data collection process. Table 1 presents descriptive statistics of subjects, including age, sex, and years of experience in this field.

Table 3.2. Subjects information

Participants	**Age**	**Sex**	**Years of experience in the construction industry**	**Years of experience in Working with CNC Machine**	**Years of experience in carpentry fields**
1	32	Male	7	8	1
2	34	Male	3	2	1
3	60	Male	30	4	10
4	38	Male	10	4	3
5	63	Male	35	1	35
6	34	Female	2	1	1
7	35	Female	5	1	1
8	33	Male	12	4	5
9	33	Male	3	1	1
10	32	Male	4	1	1

3.2.3 *Artifacts removal*

Capturing all electrical signals, including signals from other sources alongside the brain activities signals, is one of the major issues of using EEG for dynamic workload experiments (Urigüen and Garcia-Zapirain 2015). In other words, EEG signals include a large number of extrinsic and intrinsic artifacts hidden in the brain waves. Particularly, in comparison with many cognitive related experiments in which the subjects are relatively stationary, collecting EEG data in the construction industry could have considerably more artifacts signal as a result of workers' continual motion and other environmental factors. Therefore, to measure workers' mental workload/emotion, researchers had to implement artifact removal to filter the workers' brainwaves. Jebelli et al. (2018a) suggested framework was adopted in this research to remove noisy artifacts. A brief description of this framework is presented as follows:

Artifact sources can be classified into two main groups: extrinsic and intrinsic. Extrinsic artifacts refer to artifacts with sources such as sweating, drift in the electrode impedance, electrode popping, movement artifacts, environmental noise, and wiring noise in the EEG sensor. Usually, the frequency of these artifacts differs from the brain activity signals. As a result, many extrinsic artifacts can be eliminated by filtering out the frequencies of the EEG signal spectrum. A band pass filter with a higher cutoff frequency of 64 Hz (low-pass filters that pass frequencies lower than 65 Hz) and a lower cutoff of 0.5 Hz (high-pass filters that pass frequencies higher than 0.5 Hz) was used to eliminate much of the current extrinsic artifacts that induce sluggish and fast shifts in EEG signals. 0.5 Hz was selected as the lower cutoff criteria considering the frequency range of brain rhythmic potentials found by the head's surface electrodes. On the other hand, given the EEG data recording rate (128 Hz) and Nyquist frequency, which is the maximum frequency that we would assume to be present in the sampled data, 64 Hz was chosen as the higher cutoff criteria.

In contrast with the extrinsic artifact, intrinsic artifacts have the same frequency spectrum as brain activities. Therefore, removing these artifacts is more challenging than the prior one. Overall, intrinsic artifacts refer to artifacts with sources such as eye movement, blinking, and muscle activity (mainly muscle movement of head and neck). An independent component analysis (ICA) was implemented to detect and remove the intrinsic artifactual components found in the EEG recording signals. The ICA approach has been widely used in EEG clinical studies to identify and extract intrinsic EEG artifacts (Makeig et al. 1996; Reddy and Narava 2013; Vigário 1997). Specifically, the ICA procedure is capable of isolating EEG intestinal artifacts from the initial EEG without sacrificing the EEG signal. As a result, the research team used the ICA method to distinguish the artificial components in the EEG and then subtracted the components correlated with the intestinal artifacts to produce clean EEG data.

3.2.4 *Data Analysis for Mental Workload Demand*

The second objective of this research aimed to evaluate the mental workload demand of the workers in the formwork fabrication tasks using the CNC machine and to compare the results with mental workload demand in traditionally cutting formwork. This objective was achieved by recruiting ten subjects who have experience in both traditional carpentry and operating a CNC machine. The subjects needed to wear the mobile EEG headset and perform the formwork fabrication tasks in the two approaches. To measure the mental workload, the authors followed indicators suggested by Jap et al. (2009). The four metal workload indicators used in this paper were:

$$\text{Indicator 1} = (\theta + \alpha)/\beta \tag{3.2}$$

$$\text{Indicator 2} = \alpha/\beta \tag{3.3}$$

$$\text{Indicator 3} = (\theta + \alpha)/ (\alpha + \beta) \tag{3.4}$$

$$\text{Indicator 4} = \theta/\beta \tag{3.5}$$

These indicators assess mental workload based on the power distribution among alpha, beta, and theta bands representing the mental workload values. Chen et al. (2016a) called the indicator $(\theta + \alpha)/\beta$ as Engagement Index. Likewise, Wang et al. (2017) labeled θ/β as Vigilance (indicates how focused a person is when preforming a task.). As the collected data was in pattern of time series, researchers decided to segment the data into window sizes of 0.5 seconds. In this case potential features were selected to determine the preprocessed time-series data to underscore the specifications of mental demand. The research team followed previous studies and focused on channels which mainly used to capture electrical activates located in the frontal area(Hwang et al. 2018b; b; Jebelli et al. 2017, 2018b; Li et al. 2019; Wang et al. 2017). These channels are AF3, AF4, F3, and F4, having a significant correlation with mental activates. For each participant, the indicators $(((\theta + \alpha)/\beta,\ \alpha/\beta,\ (\theta + \alpha)/ (\alpha + \beta), \theta/\beta))$ for all four channels(AF3, AF4, F3, and F4) were measured in the two scenarios. This gives a total of 16 features which are listed as follows: AF3_ Indicator 1, AF3_ Indicator 2, AF3_ Indicator 3, AF3_ Indicator 4, AF4_ Indicator 1, AF4_ Indicator 2, AF4_ Indicator 3, AF4_ Indicator 4, F3_ Indicator 1, F3_ Indicator 2, F3_ Indicator 3, F3_ Indicator 4, F4_ Indicator 1, F4_ Indicator 2, F4_ Indicator 3, F4_ Indicator 4. Once the datasets was prepared, researchers used two different statistical approaches. Hypothesis testing using Machine Learning. Each of these methods will be discussed as follows:

3.2.4.1 Hypothesis testing using Machine Learning

Hypothesis testing using Machine Learning is the first approach aiming to demonstrate whether there is any difference between using CNC machine and traditionally cutting formwork in terms of mental demand. Parametric testing, such as t-testing and ANOVA, is the most common method used to analyze averages of two or more groups. The procedure of applying these parametric tests involves evaluating normality, equality of variances, and checking the random sample from a population(Field 2013). Nevertheless, most of the experimental tests in psychology and physiology include a limited number of participants and sometimes do not satisfy the parametric test criterion for distributional hypotheses (LaFleur and Greevy 2009). Statisticians have advocated using randomization methods such as bootstrapping and permutation tests(Edgington 1995; Gleason 2013).

The permutation test is a technique of randomization proposed by Fisher in the early twentieth century. The basic principle behind permutation simulation is to create a reference distribution utilizing resample by recalculating data statistics(Berger 2000). In detail, a permutation test is a form of resampling test used to compare values between two or more groups on a target variable (labels). The principle here is that the result distribution for all groups, whether control or experimental, should be the same under the null hypothesis. Thus, one can emulate the null by taking all of the data values as a single large group (Berger 2000). Applying labels randomly to the data points (while retaining the initial group membership ratios) results in a simulated outcome from the null (Anderson 2001). After adding the labels randomly to all data and documenting the performance statistic several times, one can compare the real observed statistic to the simulated statistic. A p-value is obtained by seeing how many simulated statistics value areas or more extreme as the one actually observed, and a conclusion is then drawn(Anderson 2001; Berger 2000; LaFleur and Greevy 2009).

In this study, researchers used of the permutation test and leveraged the accuracy of different supervised machine learning classifier algorithms. The tested algorithms included the

Support Vector Machine (SVM), the Random Forest algorithm, and the Neural Network MLP Classifier algorithm. The team choose these three classifiers to be able to verify the outcome. Specifically, SMV works based hyperplane, and maximum distance margin, Random Forest is a decision-tree based structure algorithm, and MLP works based on the perceptron and layers. These three a classifiers were chosen to evaluate whether the team could get the same results with different structures algorithm or not. In details, the team selected three classifiers representing different structures of algorithms. For these chosen classifiers, 10-fold cross-validation was used to verify the classification's accuracy; classification was carried out using 80 percent for training data and 20 percent for testing data. The team used the Sickit-learn package in python to implement permutation test, SVM, Random Forest, and MLP. Using this package enable the users to compute the accuracy while not going deep on the math of the classifiers. Each of these classifiers are briefly explained as follows:

3.2.4.1.1 Support Vector Machine (SVM):

SVM refers to a supervised learning algorithm focused on a binary-data classification problem and results in separating the data point with minimum classification error based on a hyperplane value. The value can be obtained by solving Equation 3.6 (Kumar et al. 2012; Pedregosa et al. 2011):

$$\mathrm{Min}_{\mathrm{now,b},\xi} \ \frac{1}{2} \ ||\mathrm{w}||2 \ + \ \frac{\mathrm{C}}{\mathrm{n}} \sum_{i=1}^{\mathrm{n}} \xi_i \tag{3.6}$$

$$\text{s.t., } yi \ (\boldsymbol{wTxi} + b) \geq 1 - \ , i = 1, \ldots , n$$

$$\xi i \geq 0 \ , i = 1, \ldots , n$$

Where $\boldsymbol{x1}$, $\boldsymbol{x2}$, ⋯, $\boldsymbol{xn}$ are the training data points and $\boldsymbol{y1}$, $\boldsymbol{y2}$, ⋯, $\boldsymbol{yn}$ are the labels. $\boldsymbol{w}$ *and* $\boldsymbol{b}$ are the classifier parameters. $\boldsymbol{C}$ is the user-specified tuning parameter and helps us to diminish the effect of the outliers on the training classifier. $\boldsymbol{\xi i}$ is defined as the slack variable that determines the soft-margin hyperplane classifier. In this research, the authors selected nonlinear SVM algorithms as it usually provide a higher accuracy. In the nonlinear SVM, a transform kernel function was adopted to draw the feature vector into a larger dimension feature space (m').[Φ: R $m \longrightarrow R\ m$]. Then, the transformed version of the training data points was used to find optimal SMV parameters, $\boldsymbol{w}$, and b, using Equation 3.7 (Kumar et al. 2012; Murphy 2012; Pedregosa et al. 2011).

$$\mathrm{Min}_{\mathrm{w,b,\xi}} \frac{1}{2} \left|\left|\mathrm{w}\right|\right|2 + \frac{\mathrm{C}}{\mathrm{n}} \sum_{i=1}^{\mathrm{n}} \xi_i \qquad (3.7)$$

$$\text{s.t., } yi\ ((\boldsymbol{x}i) + b) \geq 1 - \ , i = 1, \ldots, n$$

$$\xi i \geq 0 \ , i = 1, \ldots, n$$

Where both $\boldsymbol{w}$ and $(\boldsymbol{x})$ take value in $R\ m'$, the authors employed a kernel function (, $\boldsymbol{x}j$) = ( ) $\boldsymbol{T}$ $(\boldsymbol{x}j)$, instead of explicitly computing the transformed version of training data. Different kernel functions such as trivial, quadratic, polynomial, and radial basis function kernels were examined, and after getting a preliminary result, the radial basis function kernel that provided the most prediction accuracy was chosen. After training our SVM algorithms, unlabeled data point $\boldsymbol{u}$ can be classified using Equation 3.8.

$$(\boldsymbol{u}) = \begin{Bmatrix} 1\ if\ wT\Phi(u)\ +\ b\ \geq\ 0 \\ -1\ if\ wT\Phi(u)\ +\ b\ <\ 0 \end{Bmatrix} \qquad (3.8)$$

3.2.4.1.2 Random Forest (R.F.):

Random Forest (R.F.) is a meta estimator algorithm that suits a number of decision tree classifiers with numerous sub-sample of the dataset and uses averages to boost predictive accuracy while controlling over-fitting (Pedregosa et al. 2011). In other words, R.F. is an ensemble of multiple decision trees. R.F. is designed according to a method of bagging which utilizes parallel estimators for each decision tree (James et al. 2013). R.F.'s results are drawn on the consensus vote of the results collected from each decision tree. (Murphy 2012; Pedregosa et al. 2011). Overall, RF is mainly used due to its simplicity, high accuracy, and diversity in the problems. A simplified explanation of R.F.'s math steps behind is as follows (Friedman et al. 2001):

For b = 1 to B: (a) Drawing a bootstrap sample Z∗ of size N from the training data; (b) Growing a random-forest tree T_b to the bootstrapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size n_{min} is reached. Then, (i) Selecting m variables at random from the p variables; (ii)Picking the best variable/split-point among them; and (iii) Splitting the node into two daughter nodes.

If the $\hat{C}_b$ (x) is the class prediction of the b_{th} random forest tree, then $\hat{C}^{B}_{rf}$ (x) = majority of vote $\{\hat{C}_b (x)\}^{B}_{1}$

3.2.4.1.3 Multi-layer Perceptron (MLP):

Multi-Layer Perceptron (MLP) is a supervised learning algorithm that learns a function $f(.)$: $R^m \rightarrow R^o$ by training on a dataset, where m is the number of input dimensions and o is the number of output dimensions(Pedregosa et al. 2011). MLP is primarily used because of its capacity to both train nonlinear models and learn real-time models (on-line learning). This classification process optimizes the log-loss function with stochastic gradient descent (Pedregosa et al. 2011). Given a set of features $\boldsymbol{x1}, \boldsymbol{x2}, \cdots, \boldsymbol{xn}$ and a target y, it can learn a nonlinear function approximator for either classification or regression. It is distinct from logistic regression in that there may be one or two nonlinear layers, called hidden layers, between the input and the output layer (Pedregosa et al. 2011).

The first layer, known as the input layer, consists of a set of neurons $\{ i|\boldsymbol{x1}, \boldsymbol{x2}, \cdots, \boldsymbol{x}m \}$ representing the input features. Each neuron in the hidden layer transforms the previous layer's values with a weighted linear summation $\omega 1x1+\omega 2x2+\ldots+\omega mxm$, followed by a nonlinear activation function $g(.)$: R → R - like the hyperbolic tan function. The output layer receives the last hidden layer's values and transforms them into output values (Pedregosa et al. 2011).

As stated, this study's key purpose was to prove whether there are major variations in the mental workload demands in the two CNC and manual cutting approaches. Therefore, the null hypothesis was highlighted as there is not any difference between the mental workload demands in the two experiment while the alternative hypothesis was that there is a difference in mental demands of the two experiments (Alpha =0.05). To evaluate this statement, the research team first applied each of these classifiers to the data (indicators) and obtained the accuracy of classifying CNC mental demand vs. manually cutting mental workload demands. Then, they permutated the data (relabeling the original data) for thousand times, implemented the classifiers on the freshly generated data, and got the accuracy of each classifier in each permutation. The probability of the actual accuracy was evaluated based on the thousand permutated accuracy distributions obtained from the permutation test. In the end, they compared this probability with 0.05 to make a conclusion about the hypothesis.

3.2.4.2 Mixed Effect Model

Mixed effect modeling is the second statistical approach indicating which experiment require more mental activity considering the subjects experience. In other words, mixed model method not only helped the researcher by demonstrating which approach (CNC machine or manually cutting) required more mental activity, but it also allowed the researcher to evaluate the mental workload considering subjects' experience. The research team assumed that experience would impact the mental workload demands of performing the two scenarios' tasks. Therefore, the impact of the experience was especially considered. To this end, the research team adopted a mixed model statistical method. A mixed-model is an extension of simple linear models by allowing the inclusion of both random and where the level of the element reflects a random subset of a wider group of all potential levels (Bilder and Loughin 2014; Gałecki and Burzykowski 2013; Shrikanth 2020). Mixed models are particularly helpful when dealing with within-subjects research as it functions well under the presumption of ANOVA that data points are independent of each other (Shrikanth 2020). In a within-subjects design, one participant provides multiple data points, and those data will correlate with one another because they come from the same participant. The use of a mixed model thus helps one to systematically adjust for heterogeneity at the item level (within-subjects) and variability at the topic level (within groups) (Shrikanth 2020). The mixed model implementations are highly suggested in studies that collect several observations over time (longitudinal, time-series) or multiple experiments per participant (in subjects). Following is the general form of the mixed model:

$$Y = \text{Fixed Effect} + \text{Random Effect} + \text{Error} \tag{3.9}$$

Where fixed effects refer to a model with fixed or non-random quantities as the model parameters (observations are independent). Random effects, on the other hand, is a statistical model of random parameters(Bilder and Loughin 2014). In a mathematical representation:

$$y = X\beta + Zu + \varepsilon \tag{3.10}$$

Where y is a vector of responses, X represents a known design matrix of the fixed effects, β refers to an unknown vector of fixed effects parameters to be estimated, Z denotes a known design matrix of the random effects, u demonstrates an unknown vector of random effects, and ε indicates an unobserved vector of random errors (Gałecki and Burzykowski 2013).

According to the aforementioned materials, the research team developed mixed models using the LMER package in R to show the differences in the required mental workload demands when using the CNC machine for formwork fabrication and the traditional way. Particularly, four models, each of which for one of the indicators as the dependent variable, were generated (the average of each indicator for the four channels were used for this purpose). In other words, to develop the four models, the dependent variable were:(1) mean(AF3_ Indicator 1, F3_ Indicator 1, AF4_ Indicator 1, F4_ Indicator 1); (2) mean(AF3_ Indicator 2, F3_ Indicator 2, AF4_ Indicator 2, F4_ Indicator 2); (3) mean(AF3_ Indicator 3, F3_ Indicator 3, AF4_ Indicator 3, F4_ Indicator 3); (4) mean(AF3_ Indicator 4, F3_ Indicator 4, AF4_ Indicator 4, F4_ Indicator 4)

The findings of these statistical analyses appear in the result sections.

3.2.5 *Validation for Mental Workload*

To validate the obtained results, at the end of the experiment, subjects filled a NASA TLX survey, which can measure tasks' mental workload demands subjectively. NASA-TLX is a synthetic and subjective workload measurement method for the overall task load estimation(Hart and Staveland 1988) (AppendixA). It was developed by the National Aeronautics and Space Administration of the United States and has been significantly adopted by researchers to assess physical and mental workload in past decades (Li et al. 2019; Liu et al. 2016; Puspawardhani et al. 2016). To calculate the workload, NASA-TLX uses six dimensions (mental demand, physical demand, temporal demand, efficiency, commitment, and level of frustration) (Hart and Staveland 1988). As this research's main objective is to compare construction workers' mental workload when using the CNC machine for formwork fabrication and the traditional approach, researchers just focused on the mental demand part for the two scenarios. Also, they asked the participants to rate the mental demand for each of the tasks in the two scenarios.

3.2.6 *Research Framework for Measuring Mental Workload Demand*

In summary, to gain a better understanding of the steps taken to perform this part of the research the main framework of conducting this research is shown in the following:

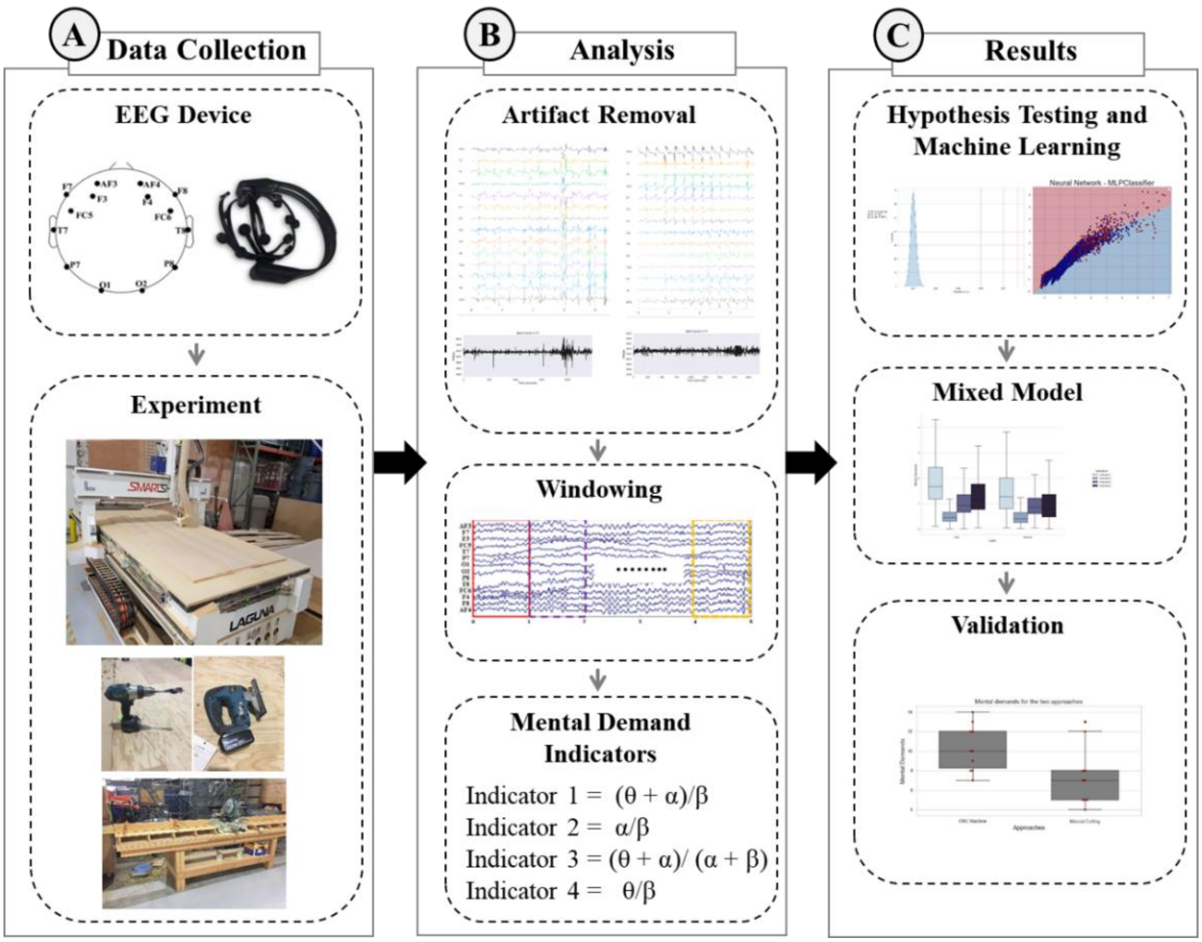


Figure 3.5. Overview of the framework suggested to compare mental workload for formwork fabrication when using the CNC machine Vs. traditional approach (cutting manually)

3.2.7 *Data Analysis for Emotion*

The objective of this research was achieved by asking the subjects to wear the mobile EEG headset and perform the formwork fabrication tasks in the two approaches. To reduce other impacts on our experiment, we will focus on just two prefabrication (controlled environment) scenarios (Cutting with and without CNC machine). To measure their emotions. In this regard, the authors will follow the Hwang et al. (2018b) approach in which they calculate valence-arousal-dominance for the two scenarios. Based on the valence and arousal calculations, the Valence-Arousal Model and Emotion could determine the amount of emotion of the workers in the two approaches(Formwork fabrication with and without using CNC machine). Valence and Arousal can be measured as follows:

$$Valence = \frac{\alpha(\mathrm{F4})}{\beta(\mathrm{F4})} - \frac{\alpha(\mathrm{F3})}{\beta(\mathrm{F3})} \tag{3.11}$$

$$Arousal = \frac{\alpha(\mathrm{AF3} + \mathrm{AF4} + \mathrm{F3} + \mathrm{F4})}{\beta(\mathrm{AF3} + \mathrm{AF4} + \mathrm{F3} + \mathrm{F4})} \tag{3.12}$$

Valence and Arousal parameter could assess the emotions based on the power distribution among alpha, and beta bands. For each subject, these parameters were measured in the two approaches (Formwork fabrication using CNC machine, and manually cutting). As shown on equations 3.11 and 3.12, AF3, AF4, F3, and F4, are the main channels needed for measuring emotions. However, as we had just two features in a time series pattern, researchers decided to develop more features in order to increase the accuracy of the analysis. To this end, the first step was to implement “windowing” procedure on our time series data. Previous studies used time-series windows from 0.25 to 6.7 seconds based on the types of actions to be monitored (Ryu et al. 2019). Researchers decided to segment the data into window sizes of 0.5 seconds. Features were selected to determine the preprocessed time-series data to underscore the specifications of workers' emotions. These features could indicate workers' emotion and would support the accuracy of the results. Authors chose the following features: (a) mean, that is, the average value of valence/arousal data in the window; (b) standard deviation of valence/arousal values in each window; (c) maximum; (d) minimum; (e) skewness, the degree of asymmetry in the distribution of valence/arousal data; (f) kurtosis, sharpness of the peak in valence/arousal data (Baek et al. 2004; Ryu et al. 2019). Overall for each participant, a total of 13 features including their experience in the two scenarios was measured to highlight their reaction (emotions). The researchers first perform a k-means clustering analysis as an Exploratory Data Analysis part (EDA) to gain a better understanding of the valence, arousal data. After the initial analysis using k-means, two main statistical approach (hypothesis testing using machine learning classifiers, and mixed effect model) was adopted to underscore the potential difference of the scenarios in terms of workers' emotion. These methods are briefly explained as follows:

3.2.7.1 K-means Clustering

The research team first used an unsupervised learning clustering (K-means) to demonstrate the data points in clusters. To this end, they choose just the valence, arousal features (mean of arousal windows, mean of valence windows) and conducted a K-means clustering to depict the location of the clusters in the two approaches on Figure 2.2. In this case, the researchers could simply interpret workers' emotion in terms of valence and arousal toward using CNC machine or cutting manually. K-means clustering is a tool for finding clusters and cluster centers in a unlabeled dataset; (A cluster is a set of data points that have been grouped together due to such similarity) (Murphy 2012; Pedregosa et al. 2011). It is mainly used to highlight fundamental patterns by grouping related data points together. K-means scans a dataset for a fixed number (k) of clusters to accomplish this goal (James et al. 2013).

The procedure of k-means algorithm begins with a series of randomly chosen centroids that act as the starting points for each cluster, and then conducts iterative (repetitive) calculations to optimize the centroids' locations (James et al. 2013). In other words, K-means iteratively shifts the centers of clusters to reduce the overall variation inside the cluster. To this end, the algorithm finds a subset of training points (its cluster) that is nearest to each center than every other center; and each features' means are determined for the data points of each cluster and this means vector for that cluster becomes the new center. It ceases generating and optimizing clusters after applying the following steps: (1) the center is stabilized or (2) the specified number of iterations was done (Murphy 2012).

3.2.7.2 Hypothesis testing using Machine learning

After the initial cluster analysis, the researcher used the data to hypothesize whether there is a significant difference in terms of emotion in the two approaches. To this end, they adopted hypothesis test stem from a machine learning prediction analysis. Similar to section 3.24.1, the researchers took advantage of the permutation test using the accuracy of a supervised machine learning classifier algorithm. To this end, they applied an Extreme Gradient Boosting (XGboost) classifier to the data, as one of the most accurate classifiers.

XGBoost is an optimal distributed gradient boosting library that has been designed for better performance, usability, accuracy, speed and portability (Quinto 2020; Sharma 2018; Sjardin et al. 2016). This algorithm works based on Gradient Boosting framework. XGBoost is a parallel tree boosting (also known as GBDT, GBM) algorithm that solves a number of data science problems easily and accurately. In XGBoost, we fit a model on the gradient of loss generated from the previous step (Sjardin et al. 2016). It is basically a modification to gradient boosting algorithm so that it works with any differentiable loss function(Sjardin et al. 2016). XGBoost resolves one of gradient boosted trees' main inefficiencies by recognizing the potential loss for all possible splits to form a new branch(Quinto 2020). In other words, this inefficiency is addressed by XGBoost, which explores the distribution of features across all data points in a leaf and uses this knowledge to limit the search area of potential feature splits (Sharma 2018). Despite the fact that XGBoost utilizes a few regularization strategies, the library's pace is by far the most valuable function, enabling users to examine a vast range of hyper parameter settings rapidly. This is incredibly beneficial, since there are too many hyper parameters to tune as they are almost always built to discourage overfitting (Sjardin et al. 2016).

As stated, one of the key purposes of this study was to prove whether there are major variations in the workers' emotion in the two CNC and manual cutting approaches. Therefore, the null hypothesis was highlighted as there is not any salient difference between workers' emotion in the two scenarios. The alternative hypothesis is that there is a significant difference between workers' emotion in the two scenarios (alpha=0.05). To evaluate this statement, the research team first applied a XGboost classifiers on the data and obtained the accuracy of classifying CNC vs manually cutting emotions. Then, they permutated the data (relabeling the original data) for thousand times, implemented the XGboost classifier on the freshly generated data, and got the accuracy of classifier in each permutation. Then the probability of the actual accuracy was evaluated based on the thousand permutated accuracies distribution gotten from the permutation test. At the end, they compared this probability with the 0.05 to make a conclusion about the hypothesis.

3.2.7.3 Mixed Effect Model

In the last step of emotion analysis, a mixed effect model was performed to highlight the potential amount of difference of emotion in the two approaches. The explanation of mixed-model was comprehensively provided in the section 3.2.4.2. According to the above hypothesis test method, the research team can demonstrate whether there is a significant difference in workers' emotion when using the CNC machine vs. when cutting the formwork manually or not. However, there were three main unaddressed research questions that the above analysis did not cover it. These questions were:

1) Is the significant difference caused by valence or arousal?
2) Which approach has higher parameter rates?
3) Does the variable experience have a pivotal impact on workers' emotion?

To address these research gaps, mixed model was adopted due to the variation in the experience of the recruited subjects. It is common that experienced carpenters prefer to continue working with manual tools instead of integrating any innovative approaches. Therefore, mixed model was employed to not only evaluate the difference of workers' emotion in the two scenarios, but it also delves into the potential impact of experience on valence and arousal .To this end, the research team developed two models each of which for valence and arousal using the LMER package in R. In each of these models valence/ arousal were assigned as the dependent variable, experience and labels as fixed effect, and participants as random effect. The findings of these statistical analyses appear in the result sections.

3.2.8 *Validation for Emotion*

To validate the obtained results, a subjective survey (a slightly changed version of the usefulness by FRED Davis (Davis 1989)) was given to the subjects asking about their emotions in the two approaches at the end of the experiment. The survey is a well-known subjective test indicating participants' behavior toward working with robots and innovation technologies. It consists of nine dimensions including likable, worthless, effective, desirable, boring, annoying, pleasant, usefulness and goodness, each of which has a Likert scale ranges from negative to positive (Appendix B). Subjects had to choose their emotions between the five Likert scales options ranging from two opposite emotional features. Since the primary objective of this research is to compare the workers' emotion in the two scenarios (manually formwork fabrication, digitally formwork fabrication), this survey was selected by the research team and then given to the subjects so that they can fill it for the both approaches. The research team asked the subjects to rank the nine main emotion indicators highlighted by to enable them with measuring valence and arousal. These indicators are Excitement, Joy, Fear, Anger, Frustrations, Sadness, Borden, Relaxation, and Contentment. Excitement, Joy, Fear, Anger, Frustration represent a high arousal while Excitement, Joy, Relaxation, Contentment shows a high valence. Based on this survey research team was able to validate their findings in this study.

3.2.9 *Research Framework for Measuring Emotion*

In summary, to gain a better understanding of the steps taken to perform this part of the research the main framework of conducting this research is shown in the following:

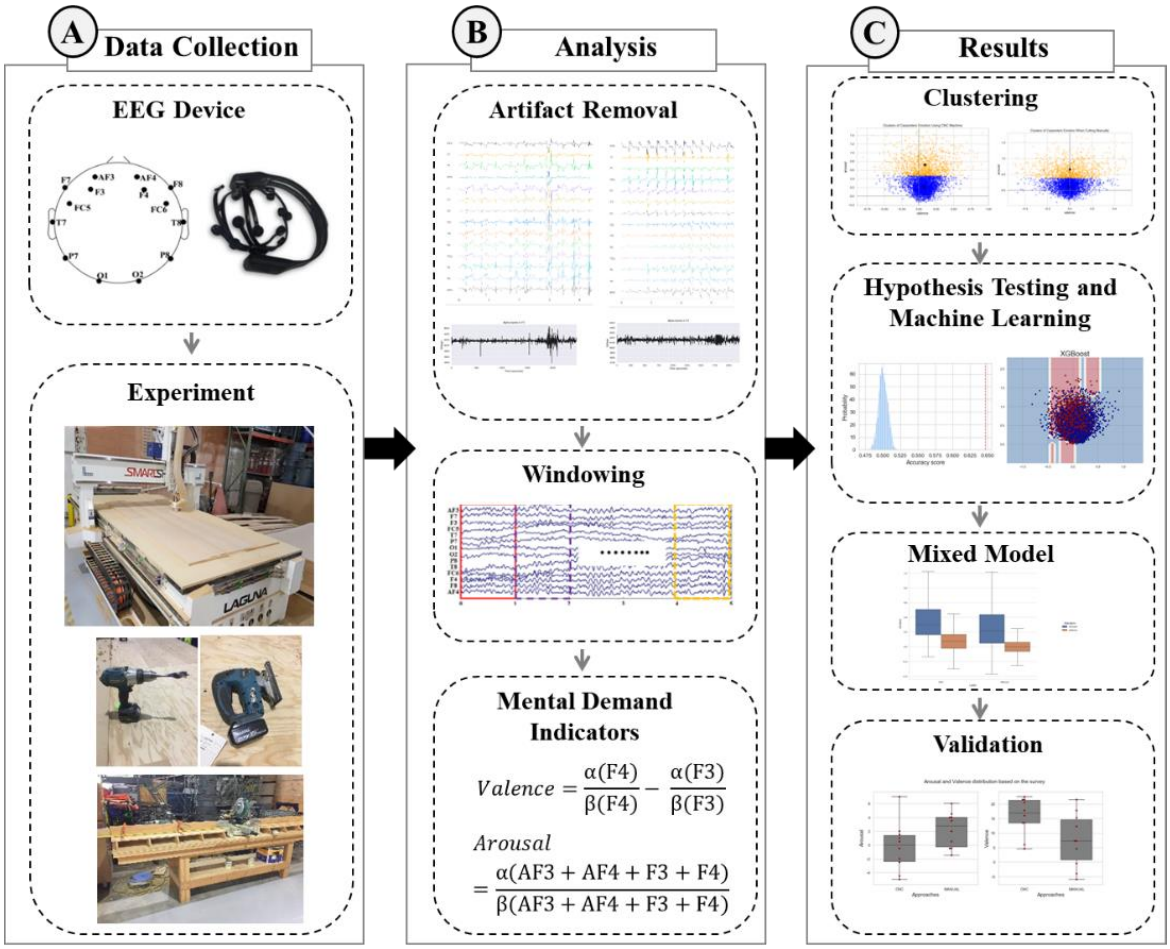


Figure 3.6. Overview of the framework suggested to compare workers' emotion for formwork fabrication when using the CNC machine   Vs. traditional approach (cutting manually)

Chapter 4. RESULTS

This study’s objectives are: (1) to first examine common design-to-installation workflows, then present an automated workflow leveraging a CNC machine, and finally evaluate the productivity of all workflows; (2) to assess workers’ mental demands during formwork fabrication activities using a CNC machine; (3) to evaluate construction workers' emotions while performing formwork fabrication tasks on a CNC machine and then equate them to workers' emotions while performing fabrication tasks on a traditional approach. Therefore, based on the above objectives, the results are divided into three main parts:

4.1 WORKFLOWS AND PRODUCTIVITY

As highlighted the study aims to introduce an automated workflow by integrating CNC machine, and then evaluate its resulted productivity rate with the traditional approaches. This objective was archived by involving the research team in seven projects over three years to observe the implemented workflow, find the gaps, and improve it. As the GC performs all concrete works in its portfolio of projects, the team was directly involved in fully implementing the projects' workflow. Figure 4.1 demonstrates general outline of the three workflows. In the following sections, the authors summarize the results and findings of the workflows:

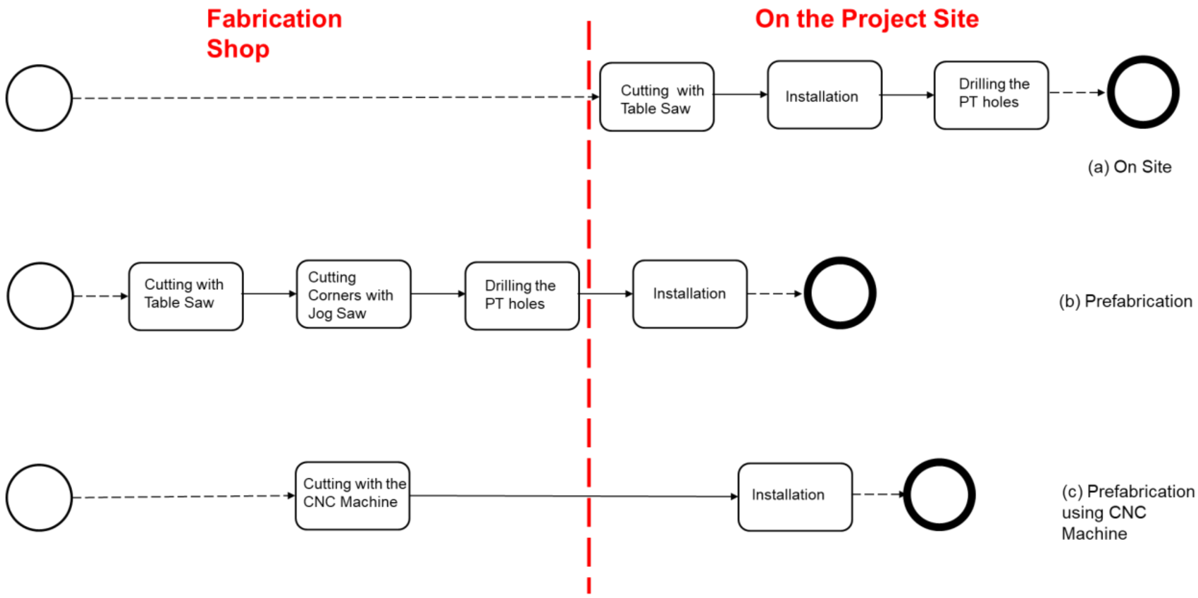


Figure 4.1General picture of the workflows

4.1.1 *The Manual Workflow in job-site*

According to the observations and interviews, the research team outlined the adopted workflow from design to installation of slab formwork in the traditional approach (manually cutting). To this end, we observed the stages of formwork fabrication at the jobsite and carried out a task analysis (Exterior Coordination and Installing). Task analysis refers to breaking them down into smaller and more manageable/measurable components. Figure 4.2 shows the workflow used in the construction projects. The interactive interviews with experts involved in this approach helped researchers to validate their findings. Each of these tasks were identified and placed in more prominent groups to comprise the workflow. The definition of each of these tasks is presented in Table 4.3.

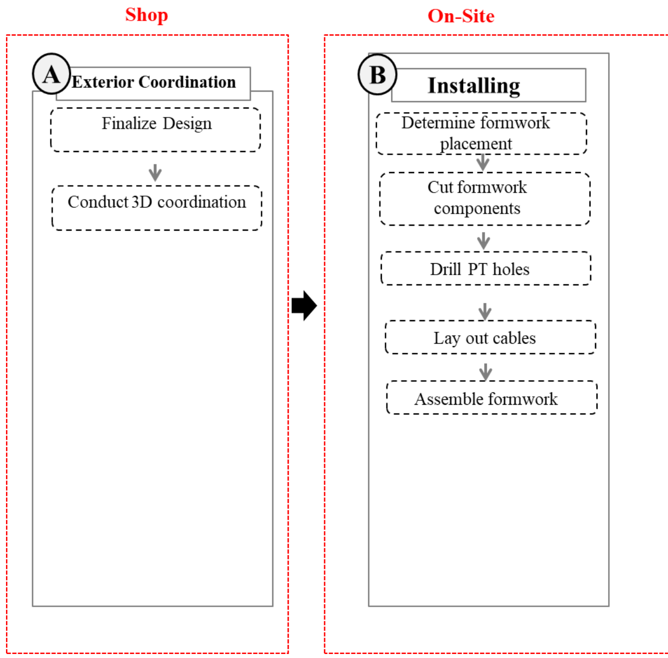


Figure 4.2.Manual workflow used at the Jobsite for fabricating slab formwork

Table 4.3.Manual workflow tasks used at the Jobsite for fabricating slab formwork

Tasks	Definition
Finalize Design	Check the design with structural engineering to ensure it is ready to go to the project team.
Conduct 3D coordination	Identify potential conflicts between the PT holes and other components in the floor.
Determine formwork placement	Place the formwork components on the planned spot.
Cut formwork components	Cut the plywood sheet using a portable table saw on the jobsite.
Drill PT holes	Drill the formwork components to create holes so that the PT cables can be installed all way through the holes
Lay out cables	Place cables on the floor
Assemble formwork	Install the cables inside the PT holes and nail the formwork components together.

In the first stage, the team refined and consolidated the 3D models and performed trade coordination specifically to vet slab location and PT components (strands, heads, and embeds). The team used ArchiCAD for modeling and Navisworks for coordination. The consolidated models captured the exterior envelope per trade (with connection embeds), concrete slabs, PT components, curbs, and pony walls. For the conflicts identified in the model, the team requested information from the structural engineer. After receiving the information and updating the model, we signed off on the final configuration and sent it to the designers for approval. After addressing the designer's supplementary information, the team finalized the model and developed an installation drawing. Carpenters used this drawing mainly for the dimensions of the floor.

All tasks were done in the Virtual Design Construction (VDC) department in the home office. After the installation drawings were given to the carpenter superintendent, the fabrication and installation-related tasks start at the jobsite. To this end, the carpentry team determined the slab formwork location on the floor. Then they cut the formwork using a portable table saw. Plywood or MDF were common materials for this purpose. Then they laid out the cut formwork components on the found location in the previous tasks. In the next step, the carpentry team drilled PT holes on the formwork components and installed the PT cables. These tasks were mainly manual and time-consuming, as sometimes the drilling was not accurate, and the team had to replace the formwork component or drilled more holes. Once the cables were installed in the formwork components, carpenters attached the components using nails. After this step, the concrete was ready to pour.

According to the observations and interviews, this manual workflow was time-consuming and led to inaccuracies in the formwork production. Working in the jobsite with all its distractions can cause inaccurate cutting of the formwork. Also, as the PT holes were drilled manually, the spot was not precise, nor were the sizes of the holes, potentially causing a need to recut. Finally, based on the team's documentation, laying out the cables and drilling the formwork to fit it was a repetitive task that increased the installation time.

4.1.2 *The Workflow in the Prefabrication Shop*

Considering the issues in the job-site workflow, the GC decided to shift the fabrication to the prefabrication shop and only send out the predrilled and precut formwork for installation. The research team, observed and documented the process of fabricating formwork in the prefabrication shop in two projects. Similar to the manual workflow on the jobsite, the research team defined the tasks necessary and interviewed experts about their findings. They also examined the benefits and disadvantages of the tasks in this workflow compared to the manual onsite method. Figure 4.3 indicates the workflow used from design to installation in the prefabrication shop.

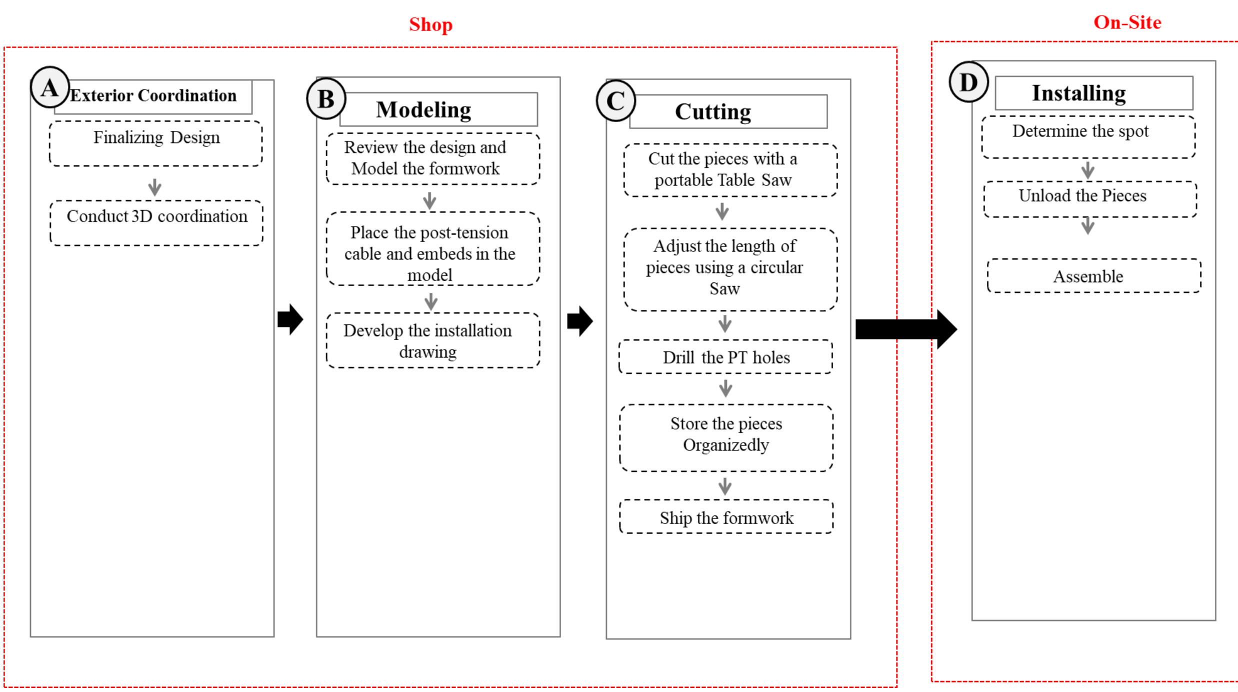


Figure 4.3.Slab formwork workflow in the Prefabrication shop

Table 4.4.Slab formwork workflow prepared in the prefabrication shop

Tasks	Definition
Review the design and Model formwork	Use Rhino to model the formwork after the final review
Place PT cables and embeds	Model the PT cables and embeds
Installation drawing	Develop the installation drawing set so that carpenters can cut plywood
Cut components	Cut the plywood sheet using a table saw, circular saw, and other tools in the prefabrication shop
Store the pieces	Store the labeled components in the installation order
Ship the formwork	Ship the stored components a day before installation.
Determine the FW location	Find the spot where the slab formwork is to be installed
Unload components	Unload the formwork components and place them in the determined spots
Assemble	Nail the formwork components together.

The design coordination section is the same as the previous workflow. After conducting the 3D coordination (clash detection), the approved model was used to virtually create formwork for the concrete slab and modeling constraints such as PT elements and related clearances. Using the software Rhino, the team modeled the formwork on the concrete surfaces. After the modeling process, an installation drawing was developed in order to demonstrate the formwork pieces on the jobsite for installation purposes. It should be highlighted that the design coordination and the modeling section, were carried out by the VDC department. Then, the drawings was given to the carpenters at the prefabrication shop. According to the installation drawing, which consists of each formwork's dimension, the carpenters cut the plywood sheet into three main parts using the table saw. Then each component was cut based on the designed length using the circular saw. Following the installation drawing, carpenters drill holes and cut notches on the components. Then, they label the component using markers and store them in an organized order so that when the crew gets the shipment, they can install each component in the order indicated in the drawing.

After shipping the slab formwork to the jobsite, the crew were first supposed to find out the locations of each labeled component and place them on the right spot. Then, they used nails to attach the components to each other.

Overall, the second workflow, manually cutting the custom formwork in the prefabrication shop, had significant advantages over the first one. However, carpenters and workers on the jobsite reported the following shortcomings: The notches' cuts in the prefabrication shop were among the most controversial issues. The notches helped the crew to assemble the components together. However, some cases said that the workers on site reported that the notches were not cut accurately, making them re-cut that component. As workers on site were not supposed to cut the formwork there, they did not have suitable cutting tools, and as a result, cutting any components postponed the installation process. Another issue regarding cutting wood using these tools was that sometimes the carpenters check the cutting areas multiple times, causing a stop-and-go process. This includes stopping the tools, checking the drawings, checking the cuts, and running the tools again. This repetitive issue had happened mainly for the inexperienced carpenters but multiple times.

4.1.3 *The Workflow Using CNC Machine*

Considering the issues mentioned in cutting the slab formwork manually, both at the jobsite and in the prefabrication shop, the GC finally decided to cut the slab formwork using a CNC machine. The research team was involved in at least five projects that adopted fabricated slab formwork using a CNC machine and observed the documented process. Similar to the second workflow, manually cutting the custom formwork in the prefabrication shop, the research team asked about the CNC machine's benefits and disadvantages in the conducted interview. Finally, based on the responses to the interviews, as well as their observations, the research team highlighted the adopted workflow using the task analysis. Figure 4.4 indicates the suggested workflow for this approach. It should be noted that the workflow was the first attempt to integrate the CNC machine for slab formwork fabrication. It aimed to improve the suggested workflow based on the identified gaps.

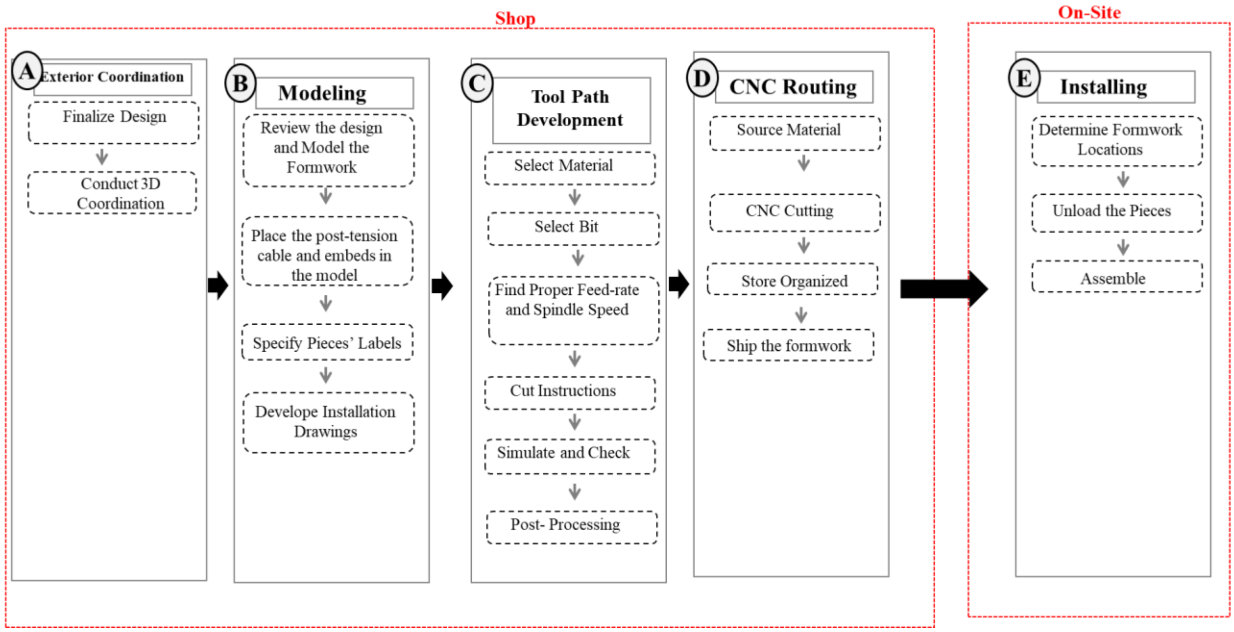


Figure 4.4. Slab formwork workflow using CNC machine

The design coordination part, as well as the modeling part, are almost the same as described in the previous workflow. For CNC tool-path development, the team had to choose a material that satisfied the formwork's required strength, as specified in the submittals. In this project, the team selected 4 ft x 8 ft MDF sheets (¾-inch thickness). Based on the material and the CNC machine's characteristics, the team had to determine the cutting bit with the appropriate federate and spindle speeds. These critical variables can influence the service life of CNC machines (Albert 2011). For cutting, the team chose a ½-inch carbide bit with two flutes. The team found that a spindle speed of 18000 RPM and a feed rate of around 400 works best for MDF formwork. To carve the label on the edge formwork, a carbide V-carve bit with a 0.745 diameter was used. Using RhinoCAM, the team simulated the cutting process, established the cutting instructions, and generated a G-code for the CNC machine.

In the CNC routing stage, for "sourcing materials," the team ordered the MDF sheets (with a week lead time) and fed them to the CNC machine. The G-code generated in the previous stage guided the cutting process. After cutting each series of mass-fabrication layout, the team stacked and organized them with labels to facilitate the shipping and assembly process. Each stack was shipped to the jobsite two days before the scheduled installation task.

Finally, the crew did the installation stage with the prefabrication approach – determining the slab formwork spots, unloading the components, and assembling the slab formwork. The definition of the tasks is presented in Table 4.5.

Table 4.5. Slab formwork workflow tasks using CNC machine

Tasks	Definition
Specify Pieces' labels	Label the formwork after modeling them in Rhino Platform
Select Material	Find an appropriate material for formwork so that it can bear the concrete weight
Select Bit	Find an appropriate bit for cutting the material based on the shape of the formwork
Find feed rate and spindle speed	Find an appropriate feed rate and bit spindle speed to increase the accuracy of the CNC cuts, as well as prevent bits' erosion.
Cut instruction	Use CAM software, implementing the instructions that we want the CNC machine to cut
Simulate and check	Check the cut instructions using simulation
Post processing	Develop the G-Code file, which will be used as an instruction translator for the CNC machine
Source material	Place the selected formwork material on the CNC machine bed
CNC cutting	Run the G-code file on the CNC machine to cut the material.

According to the crew involved in using this workflow, replacing the CNC machine for cutting slab formwork has multiple benefits. First, the quality of the slab formwork was increased, preventing reworks from the jobsite. When cutting the formwork manually, the cuts were sometimes not accurate, causing the crew to cut the formwork again. In other words, tolerance plays a vital role in view of formwork joint allowances. If the components do not fit together, cutting should be redone, which will be very costly for the contractors. In our projects, the thickness of formwork materials such as plywood is not exactly as stated. For example, ¾-inch plywood might not be the exact size. Therefore, it is possible that, even though tolerances are observed, the joints do not fit together. Adding human error to this inaccuracy leads to a rework in the formwork cut. Using the CNC machine, which has a higher precision than a manual cut, helps the project team to avoid any rework.

The other underscored benefit of using the CNC machine for formwork cuts – noted by the carpenters' superintendent – was that the CNC machine can cut the material unattended. This means that while it cuts the slab formwork, other tasks can be allocated to the rest of the carpenters.

Other benefits mentioned by the crew are reducing the need for other tools and the many safety hazards when cutting the formwork manually. However, the research team found the whole process of preparing the file for cutting by the machine is still time-consuming. The CNC machine will reduce the workload of the carpenters and add that to the VDC team. The research team tried to suggest an automated workflow by developing a user interface that took care of many modeling parts of the process to address this issue. Below is the output, including the interface in the automated workflow.

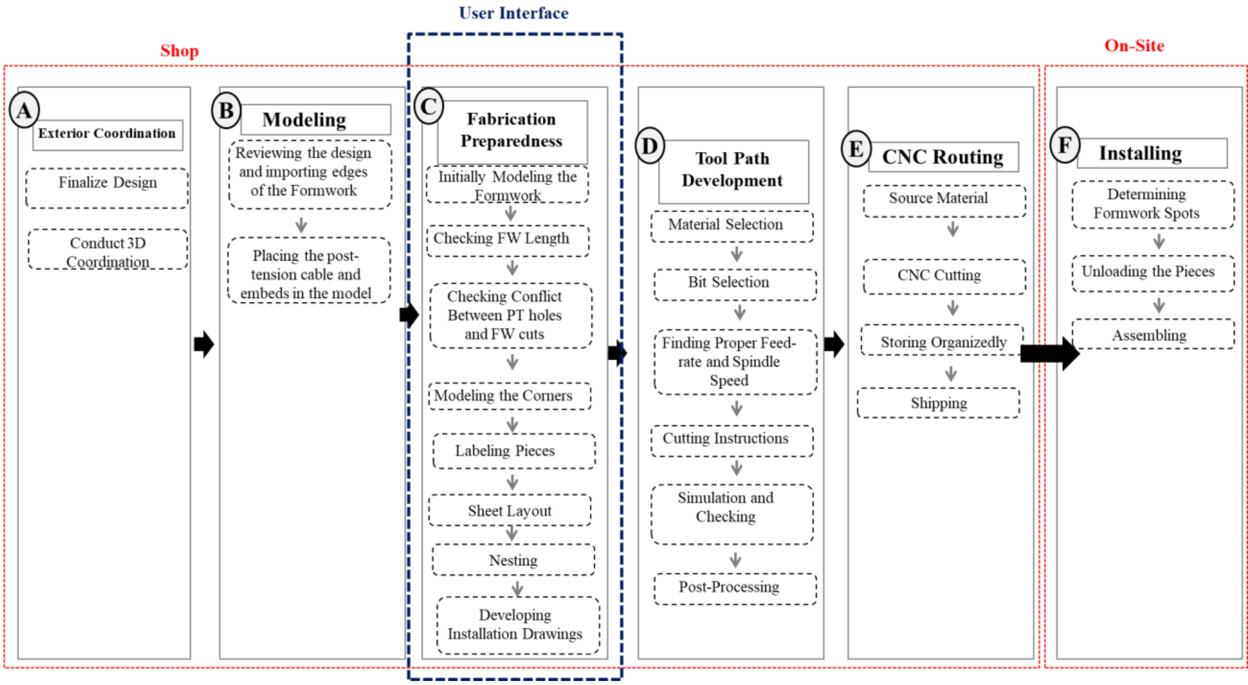
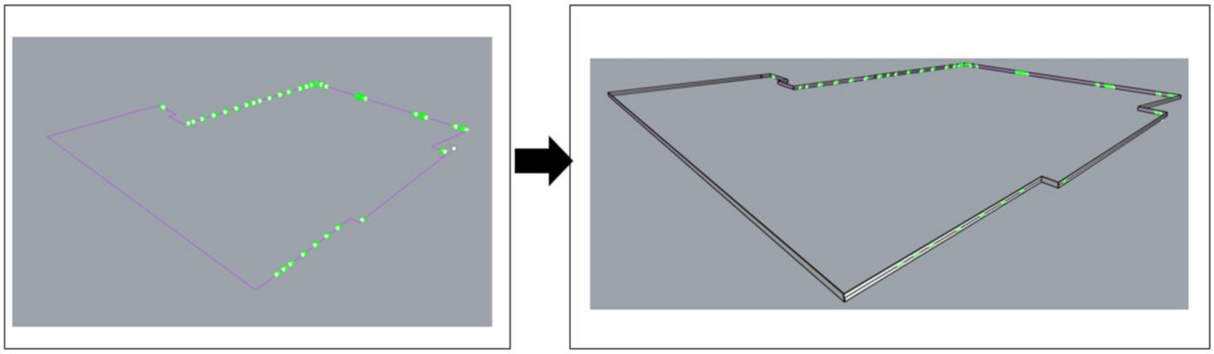


Figure 4.5. Automated slab formwork workflow using CNC machine

The research team developed a user interface to automatically execute preparation for fabrication and modeling. The user interface aimed to import the outcome of clash detection/reviewed into Rhino and finalize the model for tool path development. The approved model created virtually the formwork for the concrete slab and modeling constraints, such as PT elements and related clearances. Using the visual programming algorithm in Rhino/Grasshopper, the team picked the concrete slabs for the process, and the algorithm automatically modeled the formwork on the concrete surfaces (Figure 4.6). In other world, Figure 4.6 reveals a finalized imported model into Rhino, which will be turned to Figure 4.6(b) using the user interface.



(a) (b)

Figure 4.6. Automatically converting the curves and points representing PT holes to slab formwork.

It should be noted that the CNC bed dimension is our maximum cut size. For example, in our case, the CNC bed is 8 ft x 4 ft, indicating that each slab formwork's maximum length cannot exceed 8 feet. Also, checking for any conflict between the PT holes and the formwork cuts is of the utmost importance. None of the PT holes should be the last cut of the formwork components. As the actual cuts for the concrete formwork depend on the location of constraints (PT holes and embeds, clearances, and their variations on different floors), the allowable size for the CNC machine, and transportation considerations, the team fed the data on formwork geometries and constraints to the automation script that could parametrically address such variables and create fabrication-ready formwork cuts (Figure 4.7a).

The next task in the user interface was to identify the corners and have an extrusion from the top of one of the components and one from the bottom of the other one. To this end, any angle more than zero was identified as a corner, and the components creating the corner were recognized so that we could perform the extrusion for them (Figure 4.7b). This was an essential task, as VDC engineers usually spend a lot of time modeling these corners manually. The purpose of these extrusions is to attach them as components on the jobsite.

After cutting the developed slab formwork into components less than 8 feet and generating the corners, the user interface's next task is to label each component so that workers on the jobsite can find them. Another time-consuming task hated by the VDC engineers has been laying out the components on the sheet models (rectangular shapes) representing the CNC bed. Previously, the VDC engineers had to lay each component on the sheet, preparing that for the tool pathing stage. The research team used Python API inside Grasshopper, as well as commands in Grasshopper, to first label each component (Figure 4.7c) and then lay it out on sheets (Figure 4.7d). In this case, the user needs to open the CAM software and carry out the required tool pathing tasks.

Once the components were laid out on the sheets, the research team used a nesting algorithm obtained from the open nest package in Rhino/Grasshopper. The nesting algorithm will monitor placing the slab formwork components in the sheets to minimize waste.

The authors should note that this feature is implemented in another Grasshopper scrip. The reason was that the user interface got heavy, and there was a considerable amount of loading time for this nesting feature. In addition, workers at the jobsite receiving the slab formwork components did not like this feature; nesting will disorganize the order of storage. In this case, during the installation stage, workers had to look for all the components, as they were stacking up randomly in the formwork pile. As a result, although it will reduce the amount of waste, this feature was sometimes not used, as it will greatly increase installation time (Figure 4.8).

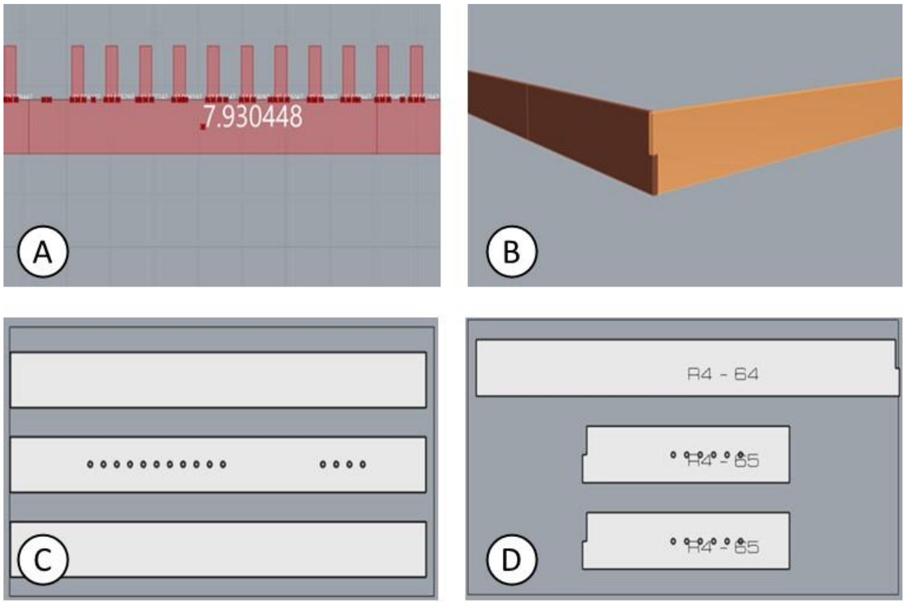


Figure 4.7. The user interface function: (a) algorithm checking whether there is a conflict between places cut and PT holes and if there has been any moving of components cut; (b) automatically generating the corners; (c) laying out the components on the rectangle with the CNC bed's dimensions, making them ready for tool pathing; and (d) automatically labeling the component on the model, as well as the laid-out ones.

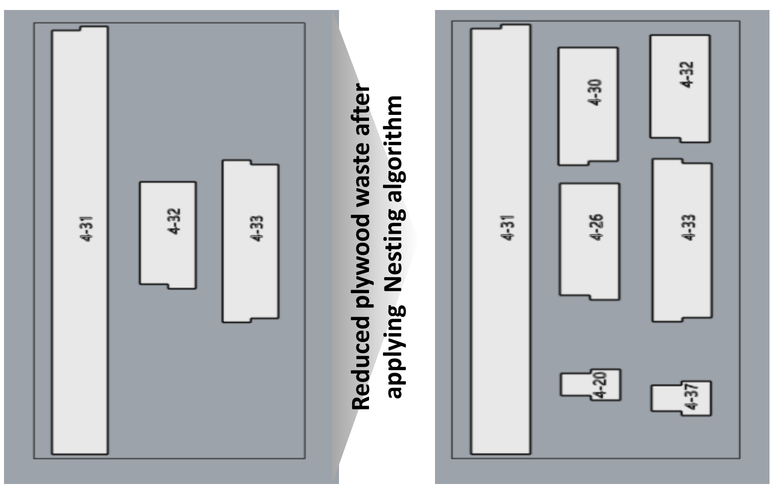


Figure 4.8. Using nesting algorithm to reduce potential plywood waste

Finally, the last task before starting the tool path procedure is to develop installation drawings. This was also considered in the user interface. Figure 4.9 is a brief explanation of the four different windows of this interface. As seen, once the user opens the interface called "Turner

Edge form," four sections can be seen on the toolbar. The first one is "Input," including all the data corresponding to the slab edge, PT holes, and the CNC bed points. The user can choose a curve indicating the slab formwork, points on the curve representing the PT holes, and a point that will lay out all the components. They can select the geometries in Rhino and press the related button in the user interface (Figure 4.9a). After selecting the geometries, the user can press the second section in the toolbar, "Dimension." In “Dimension,” the user can choose the maximum length of components, the material thickness, slab formwork thickness, tolerance between notches, PT, diameters, and the building, which can help with labeling. All these features can be selected based on building characteristics and the way the contractor wants to build the slabs (Figure 4.9b).

After determining the desired formwork characteristics, the toolbar's next step is to "Create CNC Sheets." In it, the user can convert the parametric geometries in Grasshopper (both labels and formwork) to real geometrics in Rhino. This is for all the components already laid out in the CNC beds, specified in the prior two sections. To this end, they can press the "Bake Formwork" and "Bake Labels" buttons (Figure 4.9c). Finally, the last section in the toolbar is “Create Drawing.” In it, the user can convert the parametric geometries in Grasshopper (both the labels and the formwork) to real geometrics in Rhino. This part aims to develop a section with all installation components and their labels on their model's exact spots (Figure 4.9d).

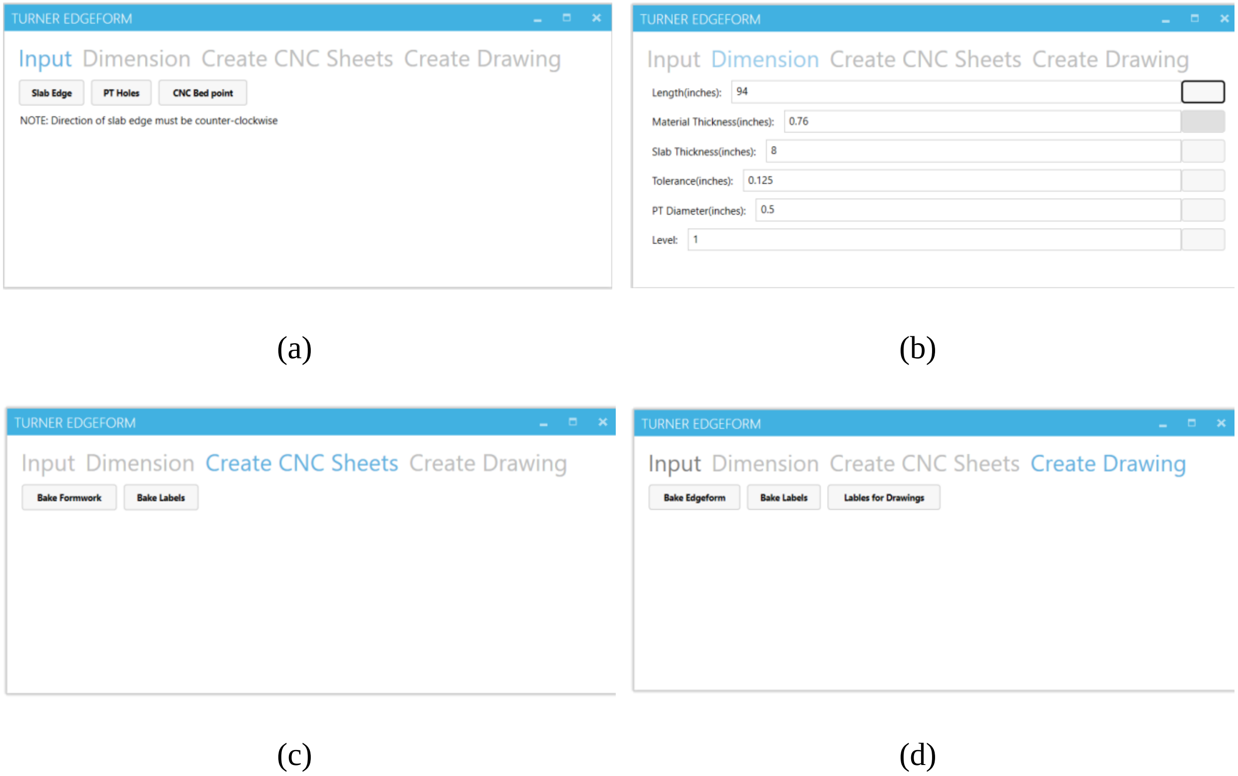


Figure 4.9. User interface outline

Overall, Figure 4.10 depicts the function of the user interface in a step-by-step approach:

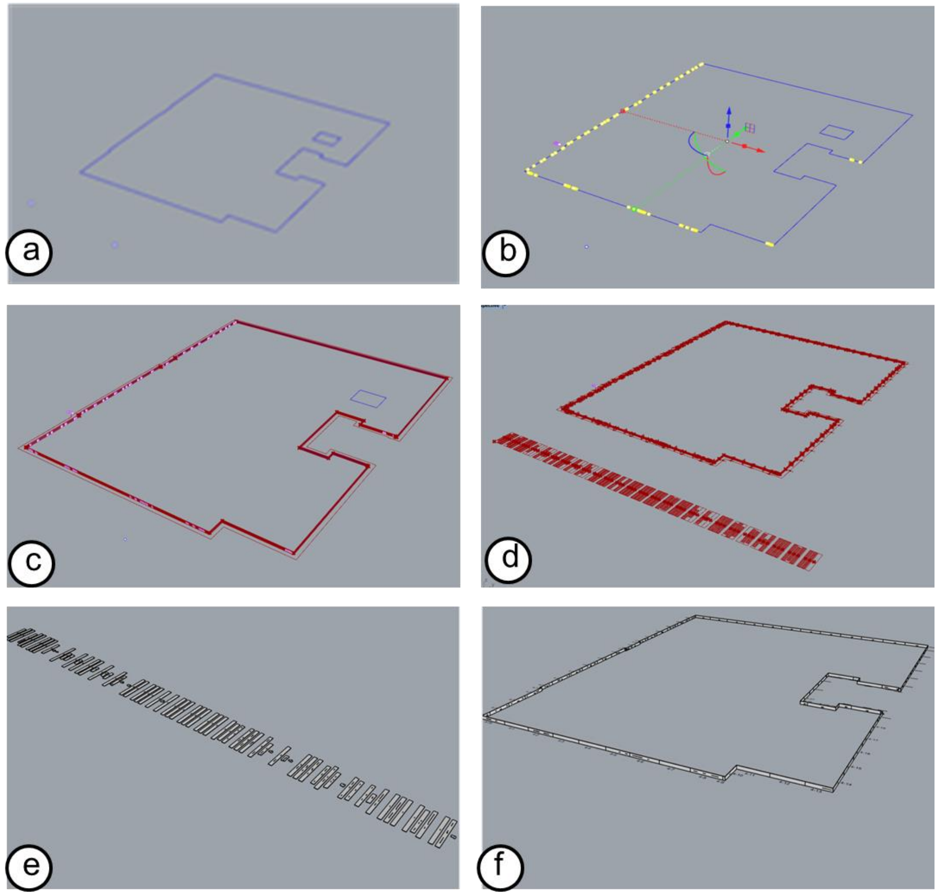


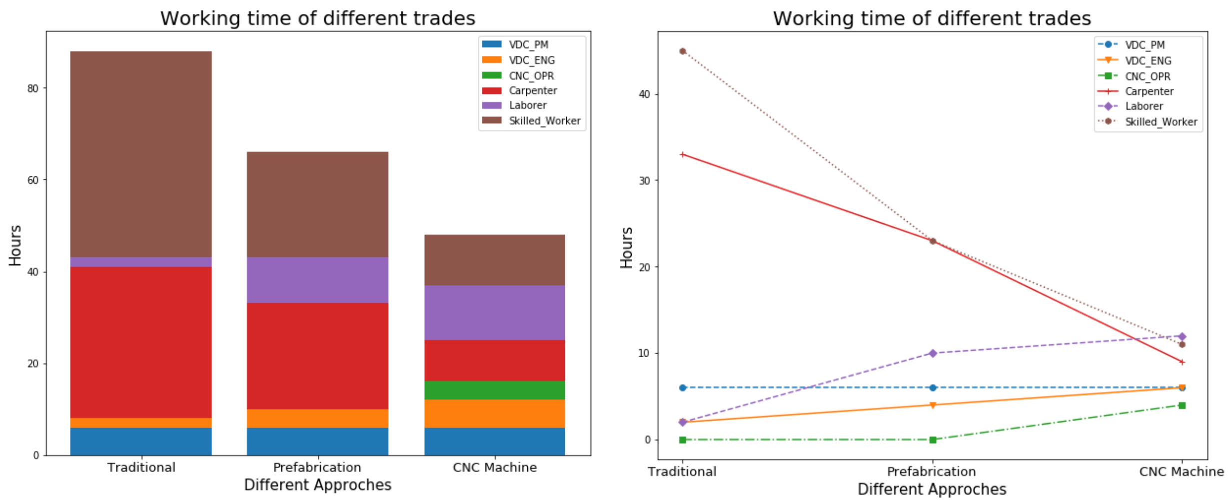
Figure 4.10. User interface steps: (a) After finalizing the model, just selecting the curve as the slab formwork (Input);(b) Selecting the PT holes imported to Rhino with the slab formwork curve(Input); (c) Slab formwork will be automatically created;(d) Selecting a random point so that the components can be layout on CNC bed in an order(Input);(f) Baking the formwork and labels. These formworks are ready to be used in the tool-pathing (Create CNC Bed); (e) Baking the formwork and labels on their exact spots. This action is implemented for developing the installation drawing (Create Drawings).

After getting to this point, the tool pathing, CNC routing, and installation stages are just as mentioned in the previous workflow. Figure 4.11 presents Figures for the CNC machine and the final installed slab formwork.

Figure 4.11. Installed slab formwork fabricated using the CNC machine

4.1.4 *Illustrative Example*

After incrementally refining the workflow in a series of field tests, the team fully implemented and validated the final workflow in an actual project, an illustrative example here. The project was a 26-story commercial building in the Pacific Northwest of the United States. The building had PT cast-in-place concrete floors. As the GC performs all concrete works in its portfolio of projects, the team had direct involvement in fully implementing the project's workflow. To validate the workflow developed and compare potential improvements using this workflow, the GC used the workflows (fabrication on site, fabricated manually in the prefabrication shop, and fabricated using the CNC machine) for three similar floors. The research team recorded the time of all tasks in each of these workflows. Time was selected as the main factor indicating the productivity in each workflow. According to Equation (1), a decrease in the time per unit of installed quantity denotes an increase in productivity. Figure 4.12 indicates this timing and the amount of time spent by different traits involved in design and installation of a floor using the three approaches. In all three workflows, laborers are mainly instructing interns or inexperienced workers who help the skilled workers, carpenters, and VDC engineers. The time spent by the VDC project managers is the same in each workflow, as we have clash detection and finalizing of the model in all.



(a) (b)

Figure 4.12. Time study on the three approaches: (a) overall timing, and (b) timing based on traits.

As shown in Figure 4.12, the time spent by the design-to-installation team for a floor in the traditional way is over 80 hours. As many people are involved in installing, drilling, and fabricating the components on the jobsite, this can happen. Specifically, skilled workers and carpenters undertook a substantial amount of these tasks (over 70 hours). It should be noted that all the time of skilled workers and almost half the time spent by carpenters are used in installation. On the other hand, this workflow has the lowest amount of planning and design before the fabrication process. Therefore, designing roles like VDC project engineer and VDC managers were not significantly involved in the workflow (less than 10 hours). According to the interview, job-site distraction, lack of tools, potential safety hazards, lack of enough workers on the jobsite during the installation time, and human errors are reasons why this workflow might take many hours of work. In the second workflow, the carpenters and skilled workers were still the main traits, having the highest working time in the design of the installation process. However, one way to explain this is that the distractions were removed in the prefabrication shop, and thereby, the time spent on this workflow was less than the previous one. Similar to the previous workflow, design-related tasks do not comprise a big portion of this timing. The main difference between this workflow and the previous one is the increased time of the laborer. One of the superintendents illustrated that in the prefabrication shop, laborers could work on tasks that on the jobsite are usually performed by skilled workers or carpenters. Overall, by transferring the workflow to the prefabrication shop, the whole workflow, from design to installation, took more than 60 hours. VDC engineers are more involved in this workflow compared to the previous version.

Finally, in the last workflow (using the CNC machine), the time spent is around 50 hours. However, as it is presented in Figure 4.12, none of the training beyond 12 hours is in this workflow, indicating a balanced distribution of working hours among all traits. Overall, using the CNC machine, a considerable number of tasks will be allocated to the design team (VDC engineers and VDC manager). They are responsible for modeling, tool pathing, and fabrication preparedness. Although adopting the user interface has helped them reduce the time, it takes around six hours per floor to perform the three stages. This could be doubled; without the user interface as modeling, the whole components could be time-consuming. As shown in Figure 4.12, the working hours of carpenters and skilled workers have sharply decreased in this workflow, as their tasks are mainly related to the installation, while in the prefabrication workflow, carpenters and skilled workers were also involved in the fabrication tasks. Laborers played a pivotal role, as they have the highest working hours in this workflow.

Table 4.6.The time spent by each trait in different workflows

Trait	jobsite (in hours)	Pre-fabrication Shop (in hours)	CNC machine (in hours)
VDC Project Manager	6	6	6
VDC Project Engineer	2	4	6
CNC Operator	0	0	4
Carpenter	33	23	9
Laborer	2	10	12
Skilled Worker	45	23	11
Sum	88	66	48

4.2 MENTAL WORKLOAD DEMAND

This study's second objective was to evaluate the mental workload demands of the construction workers in the two approaches (cutting formwork using a CNC machine and cutting the formwork manually). The authors obtained the objectives by applying the framework shown in Figure 3.5. First, to compare the difference between the mental workload demands in the two approaches, researchers measured the four indicators. Table 4.7 provides the mean, standard deviation as well as median of each of the indicators. It can be seen from the data in Table 4.7 that in indicator 1 and indicator 4, there is a potential difference in terms of mean and median in the two approaches, while no potential differences were found between their standard deviation. On the other hand, no evidence in indicators 2 and 3 was demonstrated that using a CNC machine or cutting manually influences mental workload demands. As shown in Table 4.7, the mean, median, and standard deviation of indicators 2 and 3 are almost identical in the two approaches.

Table 4.7.Simple statistics (Mean, Median, STD) about the indicators

Approach	Mental workload demands											
	Indicator 1			Indicator 2			Indicator 3			Indicator 4		
	Mean	STD	Median	Mean	STD	Median	Mean	STD	Median	Mean	STD	Median
Using CNC Machine	1.95	1.15	1.66	0.52	0.29	0.44	1.06	0.58	0.92	1.42	0.98	1.16
Cutting Manually	1.61	1.23	1.26	0.49	0.32	0.40	1.00	0.59	0.85	1.12	1.04	0.79

Figure 4.13 further revealed the distributions of these indicators in the CNC vs. Manual scenarios. As it can be seen, there is a salient difference in the Indicator 1 and 4 distributions in the two approaches. For example, the median rate of the two mentioned indicators is larger in the CNC approach (1.6 for indicator 1 and 1.1 for indicator 4) than in the manual approach (1.2 for indicator 1 and 0.8 for indicator 4), while the statistics representing other two indicators are not that that much different. The researchers then tried further to shed light on the difference in mental demands in the two scenarios using hypothesis testing as well as adopting a mixed model.

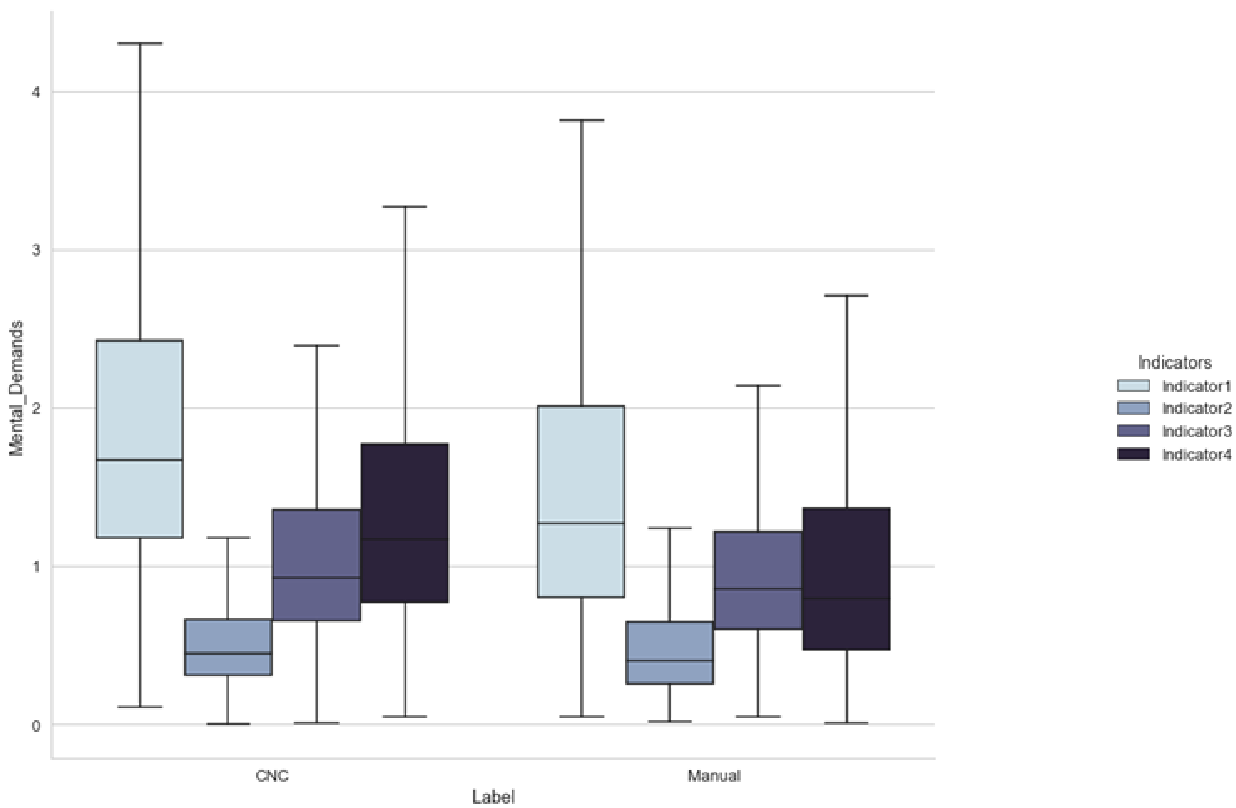


Figure 4.13.Simple box plot representing the indicators distributions

4.2.1 *Hypothesis Testing and Machine Learning for Mental Demand*

To highlight the difference in the mental workload demands in the two scenarios, the authors' utilized hypothesis testing using permutation. The assumptions therefore were: (1) H0: Mental workload demands using CNC machine = Mental workload demands Cutting Manually; (2) H1: Mental workload demands using CNC machine ≠ Mental workload demands Cutting Manually; (3) alpha =0.05. To perform this hypothesis test, the accuracy of three classifiers (Support Vector Machine, Random Forest, and MLP Classifiers) was first measured. The researchers believed that they could reject the null hypothesis if there is a significant difference between the obtained accuracy and accuracy gaining from 1000 times permutations. In other words, they shuffled the labels representing whether the experiment was related to CNC machine or traditional approach for 1000 times the (permutated the data), implemented the classifier on the permutated data in each permutation, and got the accuracy of the classifiers (It should be highlighted that the data was normalized and divided into 80% training and 20% into testing data). Then the probability of the original accuracy of the classifiers was examined with the accuracies gotten from 1000 permutations.

Figure 4.14 displayed that for the three classifiers (Support Vector Machine, Random Forest, and MLP Classifiers), the original data's accuracy is around 72%, 70%, and 73%, respectively. These values had a major difference from the accuracy distributions generated by the permutation (arrange 50%-53%). As a result, the probability achieved from these classifiers' accuracies were around 0.001, which is less than 0.05(In particular, in Figure 4.14 (b)(d)(f), the accuracies are shown with the red line, which is far from the permutated distributions). Therefore, the null hypothesis was rejected, stating that there is a difference in terms of the mental workload demands in the two scenarios.

To better understand the three classifiers algorithms, Figure 4.14 also visualizes how the major feature components were classified. The graph helps underscore that the results are not over fitted. In particular, the graph indicates the decision boundary as well as the efficiency of each classifier of a randomly chosen subset of data. To this end, the principal component analysis (PCA) method was adopted to reduce the dimensions of the calculated features to two dimensions (to visualize 16 features into two dimension, a PCA(dimensionality reduction) was leveraged). Considering the two dimensions, the authors were able to plot the features demonstrating the distinction between the two main groups. In addition, as can be seen in the Figure, the trained classifiers' models do not overfit.

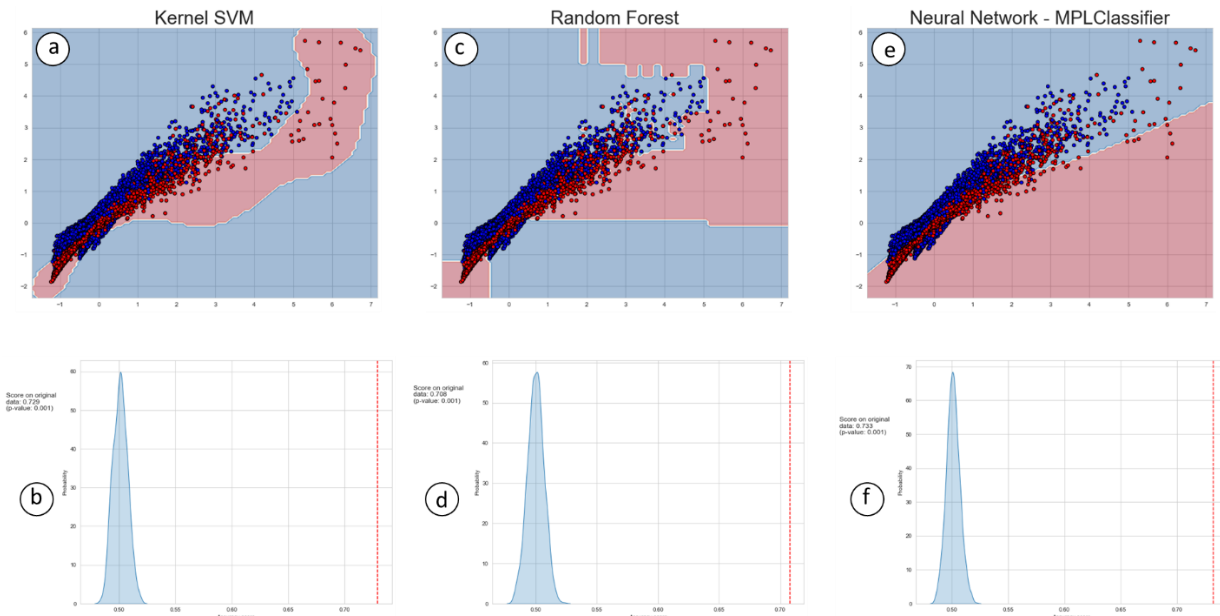


Figure 4.14. A visualization of the three classifiers and their accuracies compared the permutated ones (a) Support Vector Machine using a PCA;(b) Comparing the accuracy derived from SVM(accuracy 72%, P=0.001) with 1000 accuracies gotten from permutation test;(c) Random Forest using PCA;(d) Comparing the accuracy derived from Random Forest(accuracy 70%, P=0.001) with 1000 accuracies gotten from permutation test; (e) Neural Network MLP classifier using PCA;(f) Comparing the accuracy derived from MLP classifier(accuracy 73%, P=0.001) with 1000 accuracies gotten from the permutation test.

4.2.2 *Mixed-Model Analysis for Mental Demands*

According to the above results, it was shown that there was a different in mental workload demand in the two approaches (CNC machine Vs manual cutting). However, three main research questions were unanswered yet: (1) In which of the indicators are these difference significant; (2) Which approach (CNC machine or manual cutting) demands more mental activity; (3) Does experience influence the mental activity in the approaches. In summary, another issue came up in the research was the experience variation of subjects using CNC machine and manual tools. The researchers assumed that experience of working with either CNC machine or manual tools might be a fundamental variable potentially impacting the resulted mental workload demands. This fact is significant due to the large variety of subjects in the research. For example, two subjects had an experience of over 30 years of working as a carpenter, and thereby, cutting manually should have been easier for them.

To deal with this issue and especially highlight the experience variable, four mixed models (fixed effect as experience and labels, and random effect as participants) for each of the indicators were developed. Moreover, these four mixed morels could help the researchers to underscore which scenario demands a higher mental activity. Table 4.8 presents the results of the mixed model effects. As demonstrated in Table 4.8 Indicator1, the Label variable, which indicates the approach (CNC machine or manually cutting; Here Label means using CNC machine) and experience, is significant. This can be interpreted that in the first model, the subjects' experience has a considerable impact on the mental workload demands. Furthermore, the Label's estimated value represents that using a CNC machine will demand a 0.23 unit more mental activity than manual cutting. In details, this means that there is enough evidence in the data that for each unit increase in using a CNC machine, the Indicator1 representing mental demand will increases by 0.23 units.

Likewise, the model suggested for indicator 4 reveals a significant difference in the mental demand for the two approaches. It underscores that using the CNC machine procedure required at least 0.22 unit more mental activity than the other approach. However, in this model, the experience variable is not identified as significant, illustrating that the experience variable does not significantly influence the mental activity in the two scenarios. On the other hand, there is no enough evidence in data that the approach (using CNC machine or fabricating manually) affects the indicator 2 or indicator 3. As shown by many studies (Chen et al. 2016b, 2017; Li et al. 2019; Wang et al. 2017, 2019) , Indicator 1 and Indicator 4 might be better indicators for mental activity and as a result, we can concluded that using CNC machine could overall demand more mental activity.

Due to lack of a unit for indicator 1, and 4, increasing mental workload demand for 0.23 was not tangible. Therefore the research team decided to turn the unit to percentage. To this end, a ratio of mental demand when using the CNC machine over the mental demand when not using the CNC machine was developed. Based on this ratio, using CNC machine would increase the mental demand (Indicator1) around 14.3%, and would increase the mental demand (Indicator4) around 19.6%.

The interaction of the Label and experience was also considered in these models. However, when adding the interaction into the models, the AIC rate (Demonstrating the models' improvement) went up, and as a result, the authors did not include that in the models.

Table 4.8.Results of the mixed model

Indicator1				
Fixed Effects	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	1.670366	0.199383	8.378	9.18e-06 ***
Label	0.239591	0.062422	3.838	0.00437 **
Experience	0.008618	0.002663	3.237	0.00364 **

Indicator2				
Fixed Effects	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.5109397	0.0471715	10.832	1.1e-06 ***
Label	0.0028270	0.0213721	0.132	0.899
Experience	-0.0005213	0.0010553	-0.494	0.699

Indicator3				
Fixed Effects	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	1.071151	0.161320	6.640	0.200
Label	-0.011741	0.204828	-0.057	0.955
Experience	-0.005378	0.008545	-0.629	0.700

Indicator4				
Fixed Effects	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	1.157834	0.182464	6.346	0.000326 ***
Label	0.227074	0.050487	4.498	0.001652 **
Experience	0.009133	0.002408	3.794	0.185623

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

4.2.3 *Mental Demand Validation using NASA_TLX Survey*

To validate the experiment's outcome, a NASA TLX survey was given to the participants so that they can reflect their opinions about the mental workload demands of the tasks in the two approaches. As mentioned above, NASA TLX consists of a Likert scale of multiple questions about categories such as mental demand, physical demand, temporal demand, efficiency, commitment, and level of frustration. In this research, researchers mainly asked the participants to fill the mental workload demands parts for the CNC machine approach and one time for the manual cutting approach.

The survey results indicate that the participants believed that using the CNC machine for formwork fabrication is mentally more demanding than the manual approach. Figure 4.15

demonstrates the data statistics' boxplots, and Table 4.9 displays the mean, standard deviation, and median of NASA-TLX survey results on each approach. As mentioned, In this research, the tasks for evaluating the formwork fabrication using the CNC machine approach were (1) tool path developing, (2) sourcing materials, and (3) CNC cutting. On the other hand, the combination of (1) finding the piece's dimension, (2) cutting the piece using a table saw, (3) drilling the post-tension holes, and cutting notches create the manual formwork fabrication approach. Figure 4.15 (boxplots) and Table 4.9 are reflecting participants' opinions about the overall approaches. The median values, kurtosis, and skewness distribution can be directly read in Figure 4.15. Median values display the contribution of an item to a task's workload score; the size of the boxes reflects the kurtosis of the results of the survey as well as demonstrates to what extend the respondents have similar options on the item; the box proximity to the boundary reveals the skewness denoting whether the majority of subjects agree with a higher or lower value. As it can be seen in Figure 4.15, using the CNC machine for formwork fabrication has a higher median rate (median of CNC machine ten while the median of the traditional approach is 7) with a broader interquartile range(kurtosis). These results are consistent with the table 4.9, which presents a difference in the level of mental workload demands in the two approaches(using CNC machine and cutting manually) in terms of mean, median, and standard deviation.

Table 4.9.Impact of the mental workload demands when cutting formwork using CNC machine Vs. Manually

Approaches	Mental workload demands		
	Mean	STD	Median
Using CNC Machine	10.3	2.24	10
Cutting Manually	7.4	2.87	7

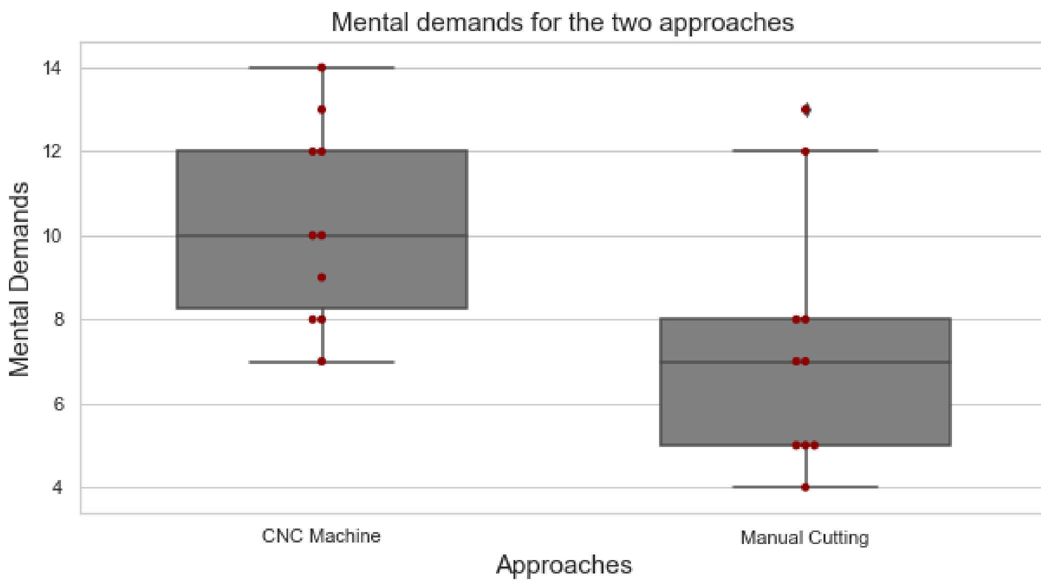


Figure 4.15. Overall rating about the two approaches in terms of mental workload demands

One of this study's main objectives is to test if there was a significant difference in the CNC machine approach and cutting manually approach. The researchers carry out a Man Whitney U-test and a Wilcoxon test on the survey data results. Overall, the CNC machine approach has a larger average of mental demand (Mean= 10.3, SD= 2.24,Median=10) compared to cutting manually approach (Mean= 7.4, SD= 2.87,Median= 7). These tests were selected to analyze the data as there were just 10 participants in the experiment, and thereby the analysis was categorized as non-parametric. Both of the tests indicated significant differences. (Man Whitney U-test, $p< 0.013^*$; Wilcoxon, $p< 0.037^*$). In other words, this outcome proves that even the participants believed that using CNC machine could significantly demands more mental demand tgan fabricating formwork traditionally.

At the end of the survey, the researchers asked the participants to rate the scale of the mental workload demands for each task in the two approaches (tool path developing, sourcing materials, CNC cutting. On the other hand, finding the piece's dimension, cutting the piece using a table saw, drilling the post-tension holes and cutting notches), too. Figure 4.16 displays the results of participants' opinions regarding the required mental demand for performing each task. As can be seen, tool path development (RhinoCam) was rated as the most mentally demanding task with an average and a median around 12.1 and 12.5, respectively. Running the CNC machine and the required related decisions were reported as the second rank in terms of the average mental workload demands. Using the table saw, and the tools which are classified in the manual approach have an average of around 7.3. It should be noted that even though these two tasks have an average rating less than the "running the CNC machine" task, their median is 7.5 (bigger than the median of "running the CNC machine") and 6.5(the same as the median of "running the CNC machine") respectively. Finding the dimensions (average of 5.7 and median of 6.0) and Lifting(Sourcing) plywood (average of 5.1 and median of 4.5) are rated as the least mentally demanding tasks. Table 4.10 and Figure 4.16 demonstrate the results of analyzing the NASA TLX survey for the tasks' mental workload demands in the two workflows.

Table 4.10.Impact of the mental workload demands when of the tasks in the two approaches

Approach	Tasks	Mental workload demands		
		Mean	STD	Median
CNC Machine	Tool Path Development	12.1	2.300	12.5
	Lifting (Sourcing) Plywood	5.1	2.69	4.5
	Running CNC Machine	8.1	3.70	6.5
Traditionally Cutting	Finding Dimension	5.7	2.32	6.0
	Using Table Saw	7.4	2.87	7.5
	Using Tools	7.2	3.65	6.5

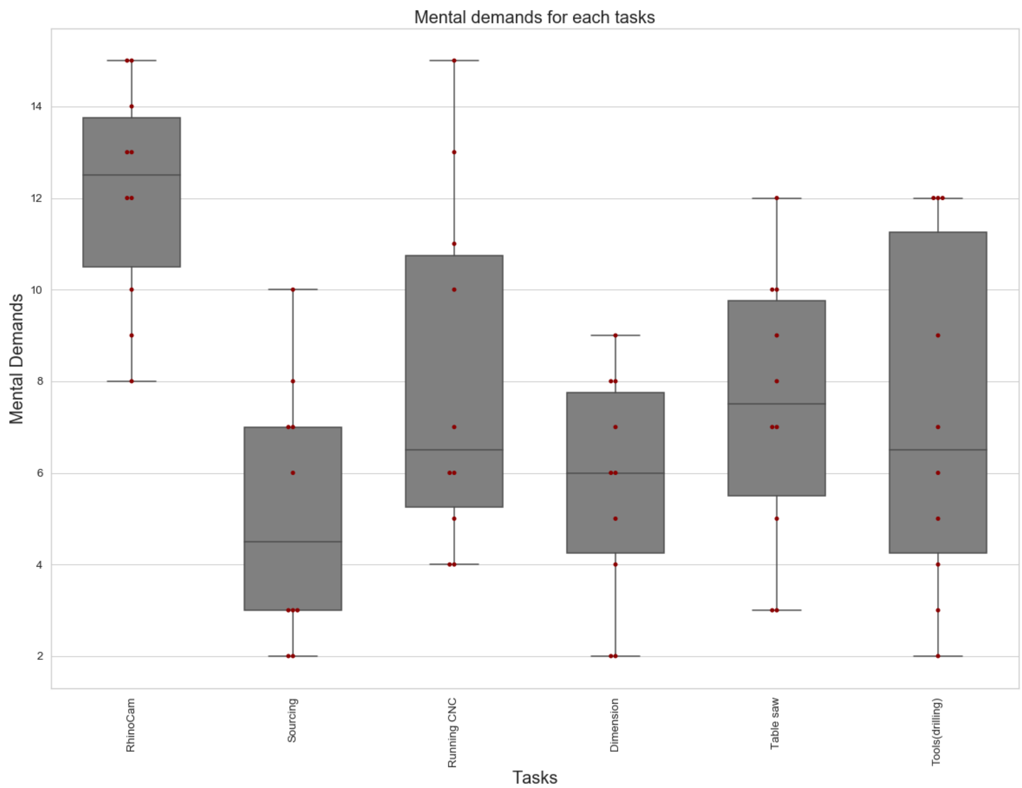


Figure 4.16. The distribution of the participants' ratings about the tasks' mental workload demands

4.3 EMOTION

This study's third objective focused on the workers' emotions in the two approaches (cutting formwork using a CNC machine and cutting the formwork manually). To this end, after cleaning the collected and removing the noise signals, researchers measured the two main emotion parameters (valence and arousal). Table 4.11 provides the mean, standard deviation as well as median of each of these parameters.

What stands out in the Table 4.11 is the salient difference in the mean score of valence in the two approaches in comparison with other values. As it can be seen, the valence mean score when using CNC machine is 0.074556 whereas the valance mean score for the manual cutting is -0.003237.

This result indicates that there seems to be a difference in the valence of the two scenario. In the same vein, the valence median score supported the above statement. The valence median score for using CNC machine was 0.076256, while this parameter was a negative number in manually cutting (-0.001625). The standard deviation of the two approaches was almost the same in the valence parameter. On the other hand, no evidence in arousal parameter was highlighted that using a CNC machine or cutting manually influences workers' emotions. As shown in Table 4.11, the mean, median, and standard deviation of arousal parameter are almost identical in the two approaches. In other words, further analysis should be undertaken to examine the difference of arousal in the two scenarios.

Table 4.11.Simple statistics (Mean, Median, STD) about the valence and arousal

Approach	Emotion					
	Valence			Arousal		
	Mean	STD	Median	Mean	STD	Median
Using CNC Machine	0.074556	0.179539	0.076256	0.362786	0.282096	0.299787
Cutting Manually	-0.003237	0.125657	-0.001625	0.270520	0.309855	0.216473

Figure 4.17 displayed a boxplot graph revealing the distributions of the valence and arousal in the two scenarios. As it can be seen, there is a considerable difference in the valence distribution in the two scenarios. For example, the median rate is larger in the CNC approach (0.07) than the manual approach (-0.001). In terms of range, the range of the valence distribution (0.75 – 0.25 percentiles) using CNC machine shows a wider range (0.18) than manual cutting (0.125). On the other hand, while the median rates of arousal in the two scenarios are close, the range in the manual cutting scenario is larger (0.388)than in the CNC machine (0.345). Specifically the 25% percentile in the manually cutting is 0.048 whereas this rate in CNC machine scenario is 0.16.

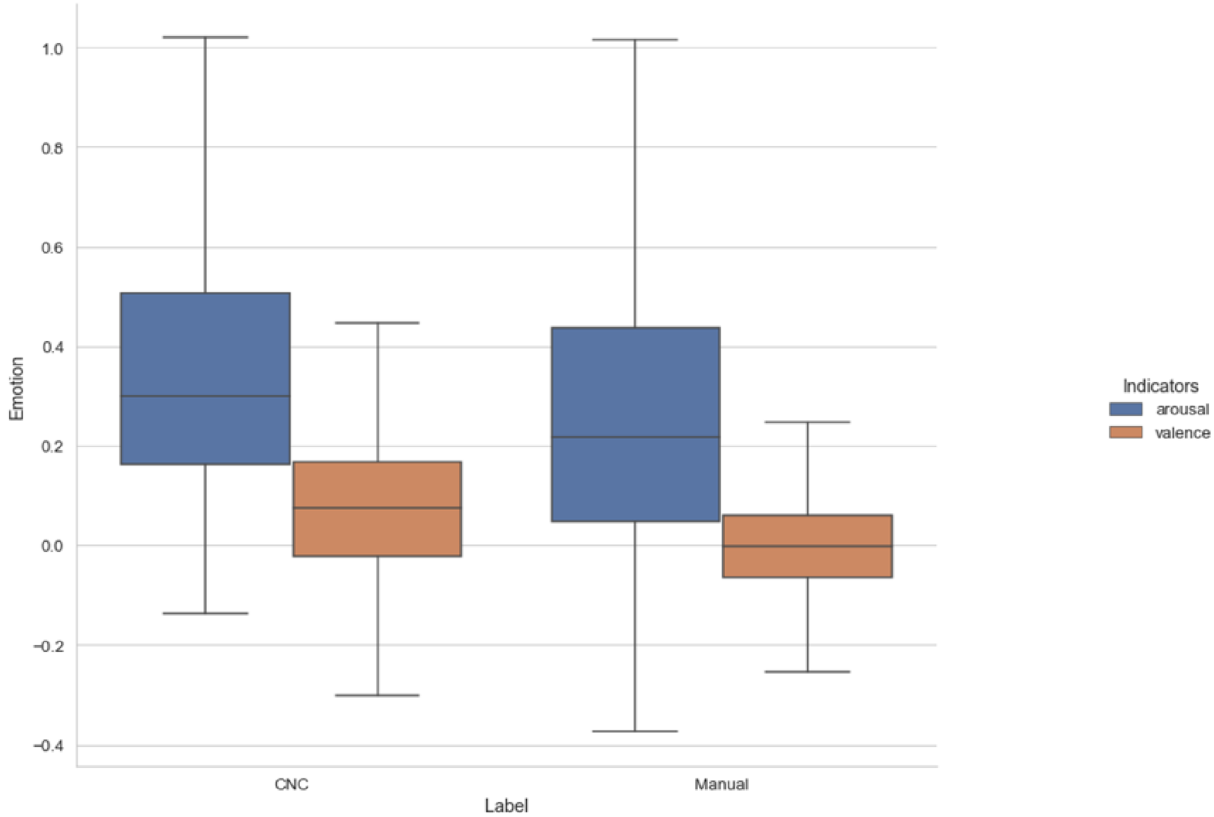


Figure 4.17. Simple box plot representing the valence and arousal distributions

In the next step of the exploratory data analysis was to examine the potential differences of worker's emotion in the two scenario; we adopted a k-means clustering. The objective of applying the k-means algorithm was to depict the clusters on Figure 2.2 and determine whether clusters are close to any of the stated emotions (Excitement, Joy, Fear, Anger, Frustrations, Sadness, Borden, Relaxation, and Contentment). As shown in Figure 4.18, researchers choose 2 clusters for each approach (CNC machine and cutting manually) using the "elbow" method (Figure 4.18 a, b). Elbow method is a practical approach helping researchers to select optimal number of clusters by fitting the model with a range of values for K. If the line chart resembles an arm, then the "elbow" (the point of inflection on the curve) is a good indication that the underlying model fits best at that point. In the visualizer "elbow" will be annotated with a dashed line.

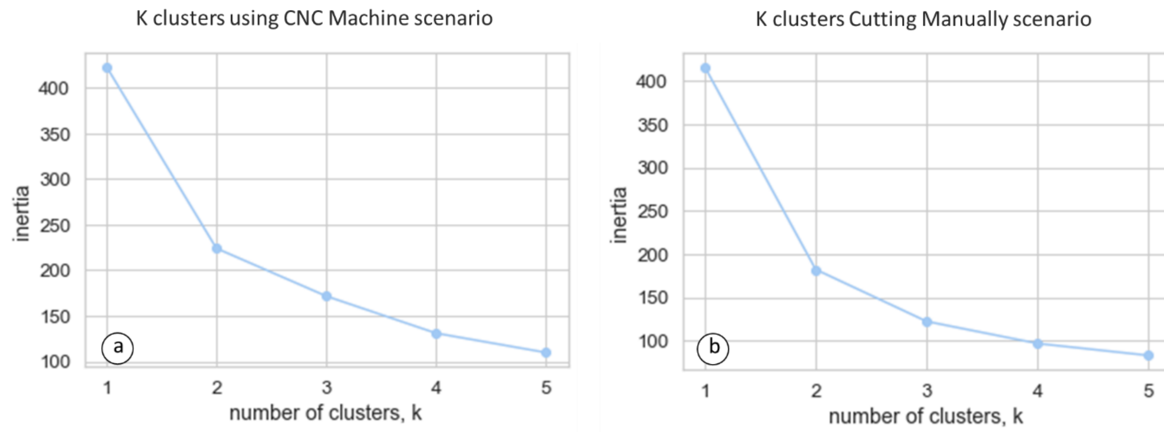


Figure 4.18. Two needed clusters for both approaches: (a) CNC machine; (b) Traditional Fabrication (Cutting manually)

The results of the cluster analysis in the two approaches are set out in Figure 4.19. Figure 4.19(a) shows that the points of the two clusters are narrower (more compact) for the emotion of workers in the CNC machine scenario. On the contrary, Figure 4.19(b) indicated a wider range of points in the clusters for manual cutting. This illustrates that workers' emotion in terms of valence were more diverse in the cutting manually approach. Also, as it can be seen, the cluster centers are inclined to the positive valence and positive arousal. Considering the figire2.2, this is close to the location of excitement and happiness/joy. Where the cluster centers were located on the arousal axis. According to the Figure 2.2, it can be drawn that the cutting formwork manually can be stem from a wide range of emotions such as excitement, happiness/joy, fear, anger and frustration. Overall, Figure 4.19 indicated that using CNC machine may increase the valence of the workers rather than cutting formwork manually. However, there might not be a significant difference in terms of arousal. To highlight this potential difference, researchers tried further to shed light on the difference in emotion in the two approaches using hypothesis testing as well as adopting a mixed model.

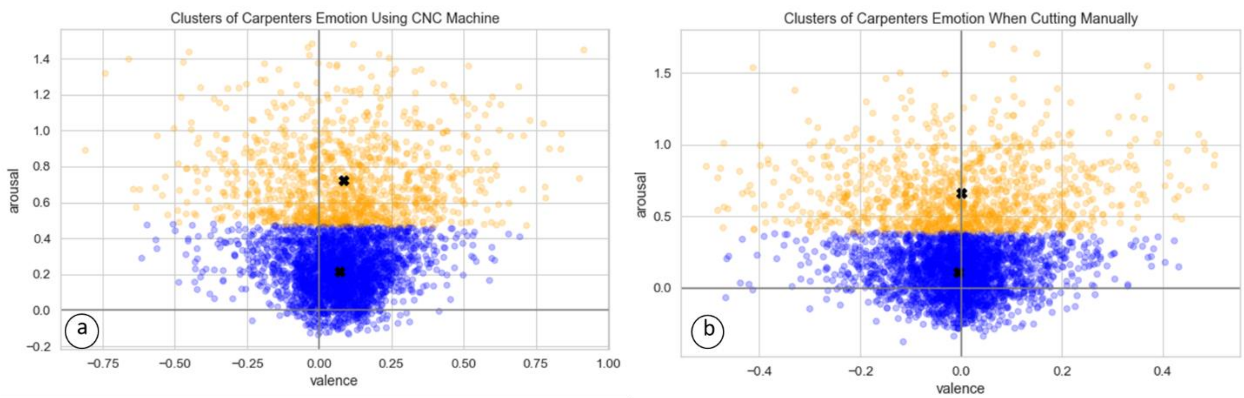


Figure 4.19. Clusters representing emotions in terms of valence and arousal (a) Using CNC machine; (b) Traditional Fabrication (cutting manually)

4.3.1 *Hypothesis Testing and Machine Learning for Emotion*

The authors used permutation hypothesis tests to point out the differences in workers' emotion toward working with the CNC machine and cutting formwork manually. The assumptions therefore were: (1) H0: there is not any difference in workers' emotion in the two scenarios (workers' emotion using CNC machine = workers' emotion in Cutting formwork Manually); (2) H1: there is a significant difference in workers' emotion in the two scenarios (workers' emotion using CNC machine ≠ workers' emotion in Cutting formwork Manually); (3) alpha =0.05.

To conduct this hypothesis test, the XGboost classifier's accuracy was first assessed. Using simulation methods, the null hypothesis could be rejected if there is significant difference between the obtained accuracy from the original data and accuracy gaining from 1000 times permutations. In other words, the labels (CNC experiment or Manual experiment) were shuffled for 1000 times randomly (permutated the data), XGboost was ran on the permutated data in each permutation, and accuracy was gained (It should be highlighted that the data was normalized and divided into 80% training and 20% into testing data). Then the probability of the original accuracy of the classifier was examined with the accuracies gotten from 1000 permutations.

Figure 4.20 demonstrated a summary of using XGboost classifiers for this hypothesis test. The original data's accuracy is around 65%. As it can be seen in Figure 4.20(b) ,this value had a major difference from the accuracy distributions generated by the permutation(arrange 47%-53%). As a result, the probability achieved from these classifiers' accuracies were around 0.001, which is less than 0.05 (In particular, in Figure 4.20 (b), the accuracies are shown with the red line, which is far from the permutated distributions). Therefore, the null hypothesis was rejected, stating that there is a difference in terms of the workers' emotion in the two scenarios. In Figure 4.20 (c), a confusion matrix of the classifier was also shown. Based on that, it can be seen that the type one and type two errors were around 32%. Type one error is predicting that the point is for using CNC machine while in reality it is for manual cutting. Type 2 on the other hand is the prediction of emotional data point to be for manual cutting where as it belongs to the using CNC machine scenario. Furthermore, the classifier predicting the cutting manually points 68% correctly while this value for predicting using CNC machine is around 67%. Overall, it can stated that even though the classifier does not have a high accuracy for the collected data, it is still accurate enough to reject the null hypothesis.

To better understand the three classifier algorithms, Figure 4.20(a) also visualizes how the major feature components were classified. The graph helps underscore that the results are not over fitted. In particular, the graph indicates the decision boundary as well as the efficiency of each classifier of a randomly chosen subset of data. To this end, the principal component analysis (PCA) method was adopted to reduce the dimensions of the calculated features to two dimensions. Considering the two dimensions, the authors were able to plot the features demonstrating the distinction between the two main groups. In addition, as can be seen in the Figure 4.20, the trained classifiers' models do not overfit.

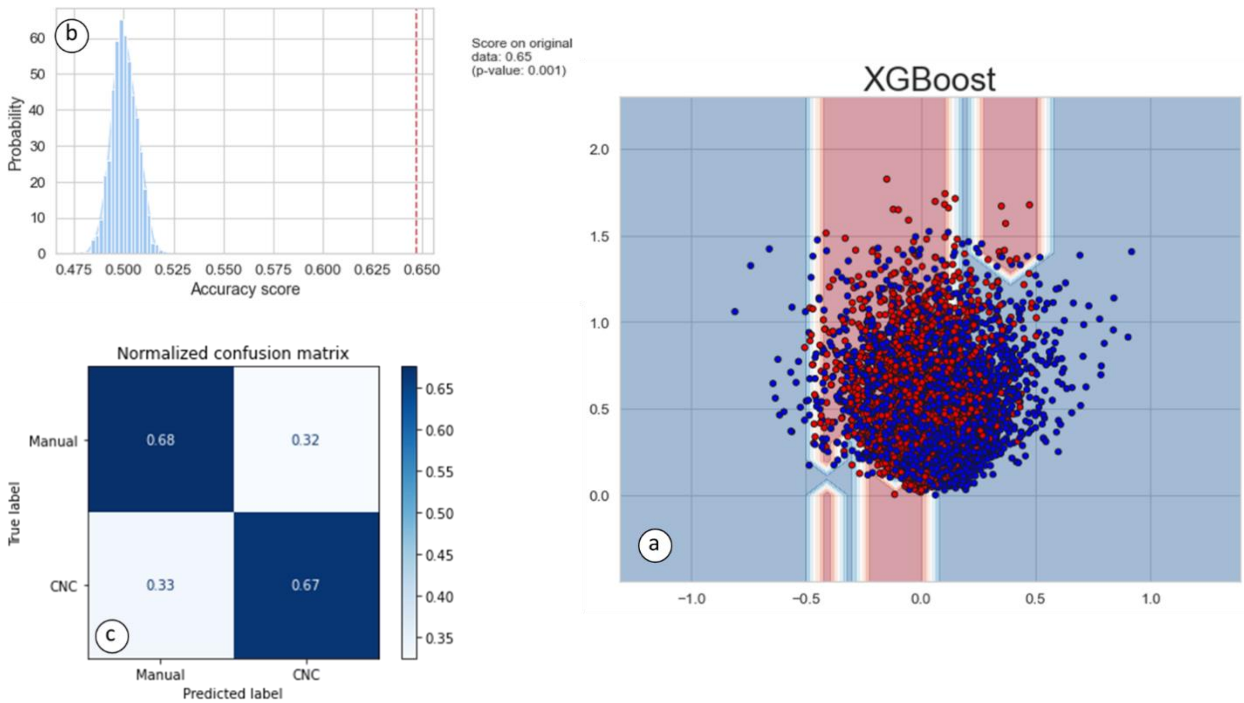


Figure 4.20. A visualization of the three XGboost classifier and their accuracies compared the permutated ones (a) XGboost using a PCA;(b) Comparing the accuracy derived from XGboost(accuracy 65%, P=0.001) with 1000 accuracies gotten from permutation test;(c) Confusion Matrix using XGboost.

4.3.2 *Mixed-Model Analysis for Emotion*

The research team was able to show a significant difference in workers' emotion by utilizing the CNC system vs. manually cutting the formwork. Specifically, to delve into questions such as, which scenario has a higher workers' emotion, which parameters cause the difference, and whether having a higher experience in one of the scenarios, impact workers' emotion, the research team adopted a mixed effect model to further explore workers' emotion in the two scenario. To deal with this issues and especially highlight the experience variable, two mixed models (fixed effect as experience and labels, and random effect as participants) for each of the parameter were developed (a model for valence, and another for arousal).

Table 4.12 presents the results of the mixed model effects. As demonstrated in Table 4.12, in the valence model, just the Label, which indicates the scenarios (CNC machine or manually cutting) is significant. This can be interpreted that the subjects' experience does not have a considerable impact on the workers' valence while the experiment (CNC machine or cutting manually) influence the subject's valence rate. Furthermore, the Label's estimated value represents that using a CNC machine will demand a 0.08 unit more valence and as a result excitement/happiness than manual cutting. On the other hand, no significant difference can be caught in the arousal model. This result supported the outcome of the cluster analysis stating that neither subjects' experience nor the experimental tasks influence the workers' emotion (arousal).

Again, due to lack of a unit for valence, saying that using CNC machine could increase valence by 0.08 does not make sense. As a result, the research team decided to turn the unit to percentage. To this end, a ratio of valence when using the CNC machine over the valence when not using the CNC machine was developed. Based on this ratio, using CNC machine would increase the valence around 7.89%.

The interaction of the Label and experience was also considered in these models. However, when adding the interaction into the models, the AIC rate went up, and as a result, the author did not include that in the models. Overall, it can be summarized that firstly, subjects' valence (emotion) might have an increase in using CNC machine scenario rather than manual cutting; secondly, the variable experience does not play a critical role in evaluating workers' emotion in the two scenario; finally, subjects' arousal parameter are almost in the same range in the two scenarios.

Table 4.12.Results of the mixed model

Valence				
Fixed Effects	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.0065707	0.0041698	6.576	0.0256 *
Label	0.0832626	0.0060966	13.657	4.2e-07 ***
Experience	-0.0030924	0.0004598	-6.725	0.501
Arousal				
Fixed Effects	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.288897	0.049502	5.836	0.000573 ***
Label	0.057425	0.035597	1.613	0.157964
Experience	0.000486	0.001667	0.292	0.817749

4.3.3 *Validation Emotion using Davies Usability Survey*

The survey results indicate that the participants believed that using the CNC machine for formwork fabrication might be more exciting/happiness than the manual cutting approach. Table 4.13 displays the mean, standard deviation, and median of the survey results on each approach. As it can be seen while in the CNC machine experiment, subjects responded to a higher valence mean score (CNC machine mean score 15.73, manual cutting mean score 7.53), it has a less arousal mean score (CNC machine mean score -0.25, manual cutting mean score 2.20). Based on the Table 4.13 values, the overall differences in the mean and median in the valence is more than the counterparts in the arousal ones. For example the difference in the valence in two approaches is around 9 whereas the same value is around 3 in the arousal. To gain a better understanding of the subjects' responses to the survey, Figure 4.21 demonstrates the data statistics' boxplots. The median values, kurtosis, and skewness distribution can be directly read in Figure 4.21.

As it can be seen in Figure 4.21, using the CNC machine for formwork fabrication has a higher median rate with a lower interquartile range (kurtosis) in the valence. On the other hand, the manual cutting approach for formwork fabrication has a higher median rate with a higher interquartile range (kurtosis) in the arousal.

Also researchers tested if there was a significant difference in the CNC machine approach and cutting manually approach using the survey. The researchers carry out a Man Whitney U-test test on the survey data results. This test was selected to analyze the data as there were just 10 participants in the experiment, and thereby the analysis was categorized as non-parametric. The test was conducted one time for the valence, and the other time for the arousal. The results show that the p-value in valence (0.027) is less than 0.05 and as a result the null hypothesis can be rejected. On the other hand, the p-value is 0.0447 in arousal which is close to 0.05. Although using the survey, the researchers can conclude that there is significant difference in the arousal too, but as the p-values is almost 0.05, it was decided to be cautious about it.

Table 4.13.Impact of the Emotion when cutting formwork using CNC machine Vs. Manually based on the survey

Approaches	Emotion					
	Valence			Arousal		
	Mean	STD	Median	Mean	STD	Median
Using CNC Machine	15.73	6.41	16.87	-0.25	3.52	0.00
Cutting Manually	7.53	9.26	7.25	2.20	2.56	2.75

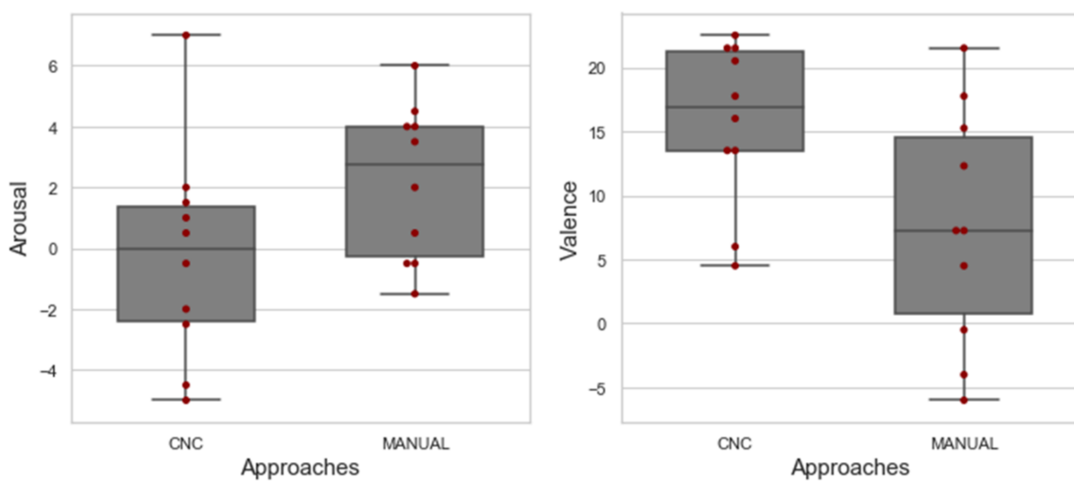


Figure 4.21. Overall rating about the two approaches in terms of valence and arousal based on the surveys

Chapter 5. DISCUSSION

In the first objective of this dissertation, the common workflows for design to installation for formwork fabrication was shown, an automated workflow was suggested and then their corresponding productivity was evaluated. The key findings of this evaluation was that using the automated CNC machine-integrated workflow saves the most time, and thereby has the highest productivity. In this study however, we compared the productivity based on collected time on two floors for each workflow. In a larger scale, for example collecting time data in different projects in a period of 10 years, the erosion of the machine could affect it performance adversely, and as a result, the obtained time could be different from what was demonstrated here. In other words, a critical factor to consider is the service life of the CNC machine referring to the estimated time of the machine under usual usage and maintenance circumstances, which is associated with the physical or mechanical conditions (García de Soto et al. 2018). For instance the cutting time will be increased as the cutting bit is getting dulled. Even this dulled bit could influence the quality of cutting causing a recut in some cases which will increase the production time of the formwork. Another significant factor to keep in mind is the robot's use limits. It could be stated that construction robots such as the CNC machine could run for 24 hours straight if the necessary tools were available. This would make the increased productivity by the CNC machine even more noticeable. However, CNC machine requires manual assistance for formwork fabrication and the idea of several working shifts has not been discussed.

It should be also noticed, that the complexity factor has not been highlighted in this study. In other words, the given slab formwork have simple shapes which is not that complicated to be cut with manual tools. In case of complex shaped formwork, it is assumed that the CNC machine productivity rate will be substantially more than manual workflows either in job site or at the prefabrication shop. In this regard, the findings of two previous studies revealed that the advantages of robotic fabrication over traditional one, improves proportionally with the structure's complexity (García de Soto et al. 2018; Labonnote et al. 2016).

Finally, the last factor receiving huge attention as well as concern by workers is whether using robots such as CNC machine would potentially be a threat to outperform carpenters' tasks. Construction robots such as CNC machine will possibly alter the existing tasks of construction project resulting in project's productivity improvement (Dowsett et al. 2018). However, using these machine will not inevitably lead to a reduction in overall employments in the long term. Routine activities are becoming less common as a result of digitalization, whereas medium- and high-skilled tasks are becoming more demanded (OECD 2016). According to previous studies, low-skilled roles like draftsman may probably develop into new high-skilled roles, especially during the transformation process, such as digital fabrication technicians to support robotic systems, digital fabrication programmers to develop computer numerical control, or digital fabrication managers (Frey and Osborne 2013; Gerbert et al. 2016). It should be also noted that on-site tasks, which involve control and rapid adoption to the field even with a low-skilled qualification would still be on demand, even with integration robotics such as CNC machine. However, the precise aspects of the digital transition in construction industry, as well as how it will impact the labor market, must be explored in the future research.

In the second objective of this study, the researchers measured the mental workload demand of using CNC machine for formwork fabrication based on four indicators, and then compared that with the needed mental workload for cutting formwork manually (traditionally formwork fabrication). In both formwork fabrication approaches (using a CNC machine and cutting manually) with ten participants, the researchers examined the impact of mental workload demands using an EEG headset. The experimental results showed that tasks associated with using the CNC machine for formwork fabrication (Tool Path Development, Lifting (Sourcing) Plywood, Running CNC Machine) could increase the mental workload demands. More specifically, the results showed that subjects exhibit a high level of mental workload demands when they perform the tool path developing task. As mentioned above, the Tool Path Development task refers to all decisions that the participants should make to instruct the CNC machine for cutting including, choosing an appropriate bit, adopting a smooth feed rate and spindle speed, determining the cut depth, specifying the order of the cuts (smaller cuts first and then bigger cuts), determining the angle of bits when entering the material, selecting the clearance space, selecting the cutting tolerance and determining the cutting direction. Making a decision about all these factors could explain why the EEG signal records were higher in this task than the other tasks.

In contrast to the CNC machine approach, findings indicated less mental workload demands in the manually cutting formwork approach (Finding Dimension, Using Table Saw, Using tool). These differences can be illustrated in part by the proximity of the experience of the construction workers who had, overall, slightly more experience in the traditional approach (cutting manually). Although the research team looked for people with experience in both approaches, there were construction workers with more than ten years of experience in carpentry fields, while their experience in using the CNC machine was maximum around five years. Therefore, it can be assumed that as the workers have more experience using the traditional approach more than the other CNC machine, they might need less mental workload demands to perform it.

In addition, among all tested classifiers, the MLP demonstrates a greater prediction accuracy. This may be attributed to MLP's high efficiency in coping with overfitting by tolerating certain misclassifications on the testing dataset. Overall, the accuracy derived from the analysis was promising because the data were collected during real tasks conducted by a construction worker in a prefabrication shop. This was one of the study's key objectives: to measure the mental workload in the real world rather than in a controlled environment. Also, researchers focused on just the approach type, and the experience of the workers when developing the mixed models. Variables, such as gender, age, physical health etc. and their interactions could be added to the model to make it more robust. In this study, however, researchers preferred to keep the mixed model simple for intuition and ease of explanations.

With regard to the method use to assess mental workload, despite the promising EEG signals data, it is still difficult to explicitly determine how working conditions and hours could impact the experiment's mental workload. Previous studies have found that many variables, including subtle physical movements, or momentary distracting thoughts, can cause sudden and substantial changes in the signals (Het et al. 2012; Mignonac and Herrbach 2004; Picard et al. 2016). Since this research was carried out in a real working environment (the construction prefabrication shop of a general contractor), it is almost impossible to fully control all the variables that could influence the participants' mental workload, regardless of the researchers' effort. However, the relationship between the subjects' mental workload and the EEG's brain activity has been well defined in the previous literature (Chen et al. 2017; Jebelli et al. 2018b, 2019b; Wang et al. 2019). As a result, this study's efforts to measure the mental workload for participants for formwork fabrication approaches are rational to gain a better understanding of the required mental workload demands for the two approaches despite all the existing obstacles that researchers face in controlling the variables in the real working environment.

Continuous measurements of the workers' mental workload in the field of this study will give enough opportunities to show how workers' mental workload differs in each task of the approaches affecting their task performance in terms of safety and productivity. Such studies could foster a better understanding of task allocation so that the project team could obtain the desired work performance. It is expected that the findings of this study could help practitioners to make informed decisions for their implementation of digital fabrication in their construction projects.

In the last objective of this study, the researchers targeted the evaluation of the workers' emotional state when using the CNC machine for formwork fabrication and compared that whit the case when fabrication formwork manually. According to the demonstrated results, the amount of valence is significantly higher when using CNC machine whereas there was not any significant difference in terms of arousal. Overall, a positive valence level results in positive emotion in a demanding environment such as the construction industry. One of the main factor that might causing this outcome could be the excitement of using a robot. In short talks that researchers had with subjects, many of them mentioned that they got excited of using CNC machine for formwork fabrication, compared to using manual tools.

Measuring valence level across two dimensions is especially considerable, as it is a more fundamental dimension representing positive emotions (e.g., excitement, happiness, contentment, or satisfaction) and negative ones (e.g. fear, anger, frustration, or depression) (Hwang et al. 2018c). This is a significant finding given the leverage of EEG. While other physiological sensors including EDA, HR, and BVP, have limited measuring power. (Jing Zhai et al. 2005; Takahashi and Tsukaguchi 2003), the EEG may be a reliable tool for measuring activities of the center of the nervous system in the field of various aspects of emotions (Lee and Hsieh 2014; Liu and Sourina 2014). Furthermore, such valence assessment is particularly important for construction workers.

Regardless of the value of arousal, a positive valence level is related to desired emotional states at construction projects, such as higher motivation, better attention, and less stress. In this vein, Grimm et al. (2007) believed that individuals with a slightly positive valence and a low degree of arousal are more likely to pay more attention and concentrate, as well as be more productive. As a result, inducing a positive valence will reduce internal stress at work, enhancing worker mental and emotional well-being. In our study, workers' valence levels are more positively influenced by the CNC machine encouraging the managers to gradually take more steps in shifting from traditional approaches in construction industry to the digital fabrication.

On the other hand, despite EEG's capability in emotion assessment, determining how using CNC machine or fabrication formwork manually influence workers' arousal levels remains a challenge. Even if the researchers attempted to monitor many of the factors that could influence arousal levels, since this research was performed in a naturalistic working setting like actual prefabrication shop, it is almost difficult to fully control all of the factors that could affect arousal levels. However, the previous literature has well-explained the association between individual arousal levels and EEG-recorded brain activity (Borghini et al. 2014; Hjorth 1975; Makeig et al. 1996; Makeig and Inlow 1993). Thus, despite all the difficulties of monitoring multiple emotion-related variables in an a real working setting, an effort to quantify both workers' valence and arousal levels in this analysis is a positive first step toward further understanding workers' emotional states in the two approaches (using CNC machine for formwork fabrication vs cutting formwork manually).

Overall The findings confirm that using CNC machine could increase the mental demands by around 17% and the valence(representing excitement) by around 7%. According to this results, this increase in mental demand could also be explained in a positive manner. In other words, according to the previous studies, high mental workload tasks in the job site could results in more human error, and accidents (Fang et al. 2016; Hasanzadeh et al. 2017). However, as the nature of the tasks would change when integrating the CNC machine at the prefabrication shop, this increse in mental demand could possibly occur due to an increase in construction workers' interest in the tasks leading to an entertaining engagement.

There are, other possible explanations about this finding. For example, Aryal et al. (2017) reported that there is a balance between mental and physical demands in performing tasks. As it can be presumed in the manual cutting, physical demands are higher than in the CNC machine approach. Thus, it can be concluded that manual cutting contains both physical and mental workload demands to some extent, while in the CNC machine approach, the weight of the demands is inclined to the mental workload rather than physical. In other words, it might be argued that the use of the CNC machine transferred the demands from physical to more mental aspects (Howell and Cooke 1989). This shift which can be indicated by a reasonable 17% increase in the mental demand, comes with a 7% enhancement in the valence. As a result, it could be concluded that even though using CNC machine could elevate the mental demand is acceptable, as the new CNC machine related tasks will increase workers' satisfaction/excitement.

This study's evaluation on workers' emotions in integrating CNC machine vs the manual approach for formwork fabrication will say a lot about how workers' emotions change regarding the two approach. Future studies may focus on how other human variables (e.g., ages, training and activities, and physical health status) and organizational factors (e.g., trades, crews, and projects) influence emotional conditions for a greater range of topics. Specifically, these variables could be added to the mixed model results for a more salient finding. Furthermore, the findings of this study encourage other researcher to conduct a more in-depth analysis into how emotions influence formwork fabrication performance, such as safety, quality, and productivity. Such this potential study will lead in determining which emotional state of workers could be a key to successfully perform the fabrication tasks.

Chapter 6. CONCLUSION

The use of digital fabrication tools is growing in the construction industry (Dowsett et al. 2018). Specifically, in the construction domain, digital fabrication tools could lead to greater control and efficiency during the building process, facilitating late-stage modifications without dramatically raising the building's cost. However, a systematic understanding of how these technologies and tools could contribute to current construction projects is still lacking. To address this gap, this study first investigated the different workflows in concrete slab formwork and evaluated how integrating digital fabrication tools such as the CNC machine could improve that. To this end, the research team studied and assessed the workflow of traditional formwork fabrication at the job site, the workflow of formwork fabrication at the pre-fabrication shop, and the workflow of formwork fabrication using the CNC machine. Overall, the first objective of this dissertation was to suggest an automated workflow using CNC machine, and then compare the productivity of all studied workflows. The study's findings indicate that adopting the automated workflow using the CNC machine could greatly reduce the time spent on developing slab formwork. As time is an indicator of productivity, the research team concluded that the new automated workflow should contribute to greater productivity of slab formwork fabrication. The example demonstrated the contrasts in use of the three workflows in separate floors of a commercial building with the same plan, supporting the authors' assertion that there are benefits to using the CNC machine’s workflow for productivity. After developing the workflows, researchers highlighted the mental demands as well as the emotional states of construction workers when using the CNC machine, and compared that with formwork fabrication in the traditional approach. To this end, ten subjects (construction workers/carpenters) performed the experimental study, carrying out CNC machine-related tasks and cutting manually related tasks in a prefabrication shop. Data was collected using an EEG while carpenters were implementing the tasks. After removing the artifacts, the research team applied hypothesis testing, including machine learning as well as mixed effect models, and was able to demonstrate that using the CNC machine procedure can demand a higher mental workload(17% increase in mental demand). Similarly, it was shown that subjects had a higher valence (emotions such as happiness, excitement) when conducting the CNC related tasks than the traditional approach(7%). In addition, to validate the result of this study, the NASA TLX (for evaluating mental demand), and Davies usability (for emotion assessment) surveys were given to the participants at the end of the experiment. The survey data analysis also confirms that using a CNC machine for formwork fabrication could increase the carpenters' mental workload demands/ emotion in comparison with the traditional approach.

One of this study's main contributions is to demonstrate that construction workers' mental workload/emotion can be measured with a wearable EEG sensor without impairing their continuous work. This is crucial as most of the previous studies tended to focus on the physical realm instead of considering the relevance of both physical and psychological facets of construction workers. The findings of this research will contribute to a thorough study by measuring continuous, accessible, and accurate real data of emotion/mental demand, which is critical to psychological aspects such as attention, incentive, decision making, attitudes, physical and mental wellbeing, etc. In detail, this study contributes to the body of knowledge of construction management by highlighting how the required workers 'mental workload demands/emotions might differ when adopting new technology and compare that with the traditional approach. It is expected that the findings of this study could help practitioners to make informed decisions for their human resource management in terms of mental workload demands/emotion in construction projects.

The authors acknowledge the limitations of this study; these can be addressed in further research. First, this research is intended to offer a precedent and not a generalizable workflow for all construction projects. The workflow was implemented for one GC, who performs concrete operations in a series of relatively similar projects. Each building component might require a different production workflow, according to a variety of factors, such as standards, local expertise, available materials, and machinery. Therefore, suggesting a comprehensive workflow implementation for all projects with multiple components may not be realistic. That is why we have tried to demonstrate the design in fabrication workflow on slab formworks using a real construction project.

Furthermore, the team used a specific CNC machine (2 × 2-½ axis), coupled with certain software and programming languages, which other contractors may or may not have intended to use. Therefore, it might be feasible for other GCs to add or remove tasks (labeling) from the workflow. This approach may be adopted for more studies so as to learn, interpret, translate, and integrate information specific to the fabrication process. These potential studies could even explore the impacts of other activities, components, and materials in the workflow. For example, other studies could try to develop a workflow using Autodesk Fusion or Sketchup and their corresponding CAM software, as well as other CNC machines (three axes, five axes), and compare the results with this study.

Further research is required to display the multifaceted effects of digital production on building processes as well. For instance, while this study focuses on evaluating an automated workflow using the CNC machine for productivity, it did not consider the performance of the workers or unexpected conditions in the different workflows. It is necessary to respond with digital fabrication tools to uncontrolled conditions and worker performance and not affect their productivity. Future research could assess the productivity of the workflow considering these underlying features to gain more specific results. Similarly, furthered research could use the resulted cost in each workflow, and assess the productive in terms of cost effectiveness.

In the second and third objectives, the researchers identified limitations as well. The number of suggested participants is not sufficient for a more comprehensive outcome. Also, the subjects were from different gender, and ages each of which could possibly affect the results of mental demands, and emotional states (heterogeneous subjects). Despite the researchers' effort in recruiting qualified participants, due to COVID 19 constraints, there were just a few people who know how to work in both approaches. Further studies could repeat the study with a larger number and more homogeneous of participants to mitigate potential biases in the findings. In addition, sometimes, the entire process of design to fabrication is performed on the project site. Further study could consider that workflow in the experiment as well and compare the results of these approaches in the prefabrication shop and the other one on the job site. Finally, in this study, researchers were not strict on evaluating the final fabricated formwork in both approaches (digitally and manually fabrication). In other words, they accepted all the final products close to the shown model to the participants. Further study could precisely evaluate the quality of final product, and assess the mental activity/emotion signal based on that. This would allow the further researchers to find mental demands/ emotions related to a high quality fabricated formwork. Despite these limitations, it is expected that the information here will support project stakeholders in their efforts to develop their own digital fabrication workflows using CNC Machines.

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APPENDIX A: NASA_TLX SURVEY

Title	Endpoints	Decryptions
Physical Demand	Low/High	How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
Temporal Demand	Low/High	How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
Mental Demand	Low/High	How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?
Effort	Low/High	How hard did you have to work (mentally and physically) to accomplish your level of performance?
Frustration Level	Low/High	How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?
Performance	Good/Poor	How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

Rating Sheet (Check on each scale at the point that best indicates your experience of the task)

Physical Demand

Low High

Temporal Demand

Low High

Mental Demand

Low High

Effort

Low High

Frustration Level

Low High

Performance

Good Poor

APPENDIX B: EMOTIONAL STATE SURVEY

#	The nine items in the emotion questionnaire	
1	Excitement	○
2	Joy	○
3	Fear	○
4	Anger	○
5	Frustration	○
6	Relaxation	○
7	Contentment	○
8	Sadness	○
9	Boring	○

VITA

Mohammad Sadra Fardhosseini was born in 1989 in Iran. He received a bachelor's degree in Civil Engineering in 2013 from Shahid Beheshti University. He earned his first master's degree in construction engineering from the University of Nebraska-Lincoln in 2016 and his second master's degree in Industrial Engineering from the University of Washington. Sadra started his PhD studies in Construction Management at the University of Washington in 2016 with a scholarship from the College of Built Environments. While pursuing his PhD, Sadra has worked as a teaching and research assistant at the University of Washington and interned at the Virtual Design Construction Department of Turner Construction Company in Seattle.