LEVERAGING MANUFACTURING HUMAN-AI TEAM INTERACTION for CYBER-PHYSICAL-SOCIAL SYSTEM CONSTRUCTION

by

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(Under the Direction of Beshoy Morkos, Ph.D.)

ABSTRACT

The advancement of Industry 4.0 is revolutionizing the manufacturing landscape. Interaction between human operators and CPS (Cyber-Physical Systems) has reached a point where cognitive collaboration is in higher demand than physical collaboration. Implementing CPSS (Cyber-Physical-Social Systems), particularly concerning human-AI interaction, can improve manufacturing productivity and efficiency. However, challenges in the manufacturing workforce nowadays point to the development of CPS lacking human consideration. Neglecting fundamental inquiries in team interaction may lead to technology implementation failures and counterproductive human behaviors, with pressing issues such as human stress, anxiety, and trust issues emerging. Actions need to be taken to construct a framework where the cyber, physical, and social components can advance at the same rate, meaning CPS should be implemented while simultaneously prioritizing human well-being. This dissertation proposes a framework for constructing a universal CPSS in a manufacturing context, where we first explore the impact of perceived AI-guided interventions on human operators' behavioral changes and decision-making processes. The AI-guided interventions are referred to as "nudges." Then, the research investigates the impact of different modalities of "nudges." Lastly, we study other factors in the manufacturing environment that can alter human operators' decision-making for positive manufacturing performance. This research contributes to optimizing the role of humans in relation to CPS support, team interaction, and human cognition. Realizing a collaborative socio-technical partnership between human operators and AI agents in CPS necessitates a comprehensive understanding of their communication and teamwork dynamics. This work promotes the synergy of human operators with CPS to facilitate informed decision-making and foster intelligent collaboration for manufacturing optimization.

INDEX WORDS: [Smart Manufacturing, Cyber-Physical-Social System, Human-AI Interaction, Industry 4.0, Operator 4.0, Nudge, Decision-Making, System Design, Operation Research in Manufacturing]

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DEDICATION

Dedicated to my family, my mom Yanhua Wang, my dad Qinghui Yang and my little sister Xiaocheng Yang. Mom and dad, being your child is the most honored achievement I've ever made. This academic achievement is a little gift from me. Thank you for being my back support all the time and for the endless love you gave, and thank you for letting me be me, being an energetic, positive, persistent, and strong girl who looks forward to future excitements.

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CHAPTER 1

INTRODUCTION

The manufacturing environment has been evolving with the emergence of Industry 4.0 elements, such as CPS (Cyber-Physical System). The involvement of advanced technologies has changed the ecosystem paradigm by overwriting the construction of the ecosystem. A higher level of flexibility is required for human in manufacturing, from assembly line operators to industrial company owners, to develop and improve their capability to adapt to the development of current manufacturing workplaces. It has become critical to restudy the construction of human-technology interaction to build a new CPSS (Cyber-Physical-Social System) framework that can be applied to industry, which has led to this research. This big research is conducted by researchers from two different fields. This dissertation focuses on the research in manufacturing performance and engineering optimization while the other researcher investigated the study from a learning and ethical perspective [1].

1.1 Research Background

The increased applications of AI (Artificial Intelligence) foreground the design principles of the manufacturing workplace environment in the era of Industry 4.0. Industry 4.0 operates through offering real-time feedback in manufacturing processes by applying advanced technologies such as CPS, cloud computing, and the Internet of Things (IoT), etc. Those advanced technologies signal a different human-AI interaction paradigm with the integrated use of AI in the manufacturing systems [2]. The complex dynamics inherent in human-AI interaction necessitate an in-depth comprehension. Little studies have been conducted on the mechanism of human-AI interaction in manufacturing workplaces.

Research on human-AI interaction explores factors correlating to the industrial human-AI team formation. AI systems with higher liability gain more trust from human for it can better assist with human decision-making processes [3], which leads to better team performance. Traditional manufacturing has evolved into smart manufacturing which requires more intelligent human-AI teams to tackle tasks with higher difficulty and flexibility, thus, the development of the current AI system differs from the traditional AI systems, focus has been given to designing cooperative AI systems to foster collaboration in building human-AI teams [4]. Nonetheless, research also shows that social factors and human psychological factors play important roles in humans' acceptance level towards AI [5]. As a result, how human operators react toward AI and AI-guided decision-making processes should be understood in smart manufacturing. This has led to the consideration of the underlying phenomenon in human-AI interaction, thus addressing the integration of both components to advance human-AI team construction.

1.2 Research Motivation

Manufacturing has traditionally been navigated in heuristics where human operators perform actions based on the traditional ways of how things have always been done. However, the advent of technology in Industry 4.0 has now allowed human operators to make informed decisions. Such collaboration, if effectively implemented could support human operators with faster and more accurate decision-making making processes, thus improving manufacturing performance in the meantime. However, there's minimal fundamental understanding of the effects of human performance within human-AI interaction in CPSS environments. Emphasis should be put on the emergence of the phenomenon between human and AI to capture the dynamic changes for better collaboration.

Technology trends simply refer to the advanced digital technological innovations that, collectively, enable the rise of the new digital industrial technology. However, the development of Industry 4.0 requires comprehensive considerations that can provide with guidelines towards an entire digital manufacturing enterprise. The capability of being able to adapt to Industry 4.0 environment is currently a top priority, but the implementation of Industry 4.0 itself is unclear, for example in the current manufacturing industry, a lot of companies are facing difficulties when they come to adjusting their problems related to working efficiency, working productivity and workforce development. CPSS was identified as important given most of the previous scientific works on Industry 4.0, considering CPSS as the key building block that glues human operators and AI technology together. Yet as CPSS is still in its infancy, the interconnection among cyber, physical and social components of CPSS necessitates the integrative collaboration to implement the manufacturing system construction. Actions need to be taken to incorporate the cyber, physical, and social elements into manufacturing [3, 4].

The fundamental architecture of CPSS is divided into three parts: cyber element, physical element, and social element. Human's role in CPSS evolves with the human-AI interaction and thus, serves as a human-centric system to facilitate manufacturing productivity in synthetic environments, which will have profound significance to manufacturing assembly line collaboration optimization. Considering the potential impact of the role of human in I4.0 [8], the fundamental step is to formally incorporate human aspects when implementing CPSS in manufacturing [9]. This is a critical area of research necessary as we consider manufacturing's shift toward a cyber platform [10], [11].

While there are many elements of CPSS that can and must be investigated, this research attempts to improve human-AI team performance in manufacturing assembly line environments, by considering human operators' manufacturing production rates using an intervention called the "nudge" approach in the manufacturing assembly line. Nudge refers to the directing of human's choices toward a behavioral change by deliberately designing the decision architecture. It is widely applied in the current manufacturing workplaces, many cyber-physical systems interfere with human through nudges, and these nudges are not well understood. We hypothesize the involvement of the nudging strategy and different modalities of nudges (visual, auditory, or somatic) can affect manufacturing operators' production rates. Manufacturing production rates in the assembly line can be evaluated through quantitative data including but not limited to throughputs (the number of products passing through the assembly line), manufacturing defects (incorrectly attached parts, improperly manufactured pieces, incorrect bolts or fasteners) and time used on each workstation before and after being nudged. By reading the data collected in a computationally statistical way, whether there is any difference among individuals and groups in perceiving the sudden changes triggered by nudge devices can be observed. Manufacturing performance classifications for each workstation regarding different interventions can be made by using computational models, hence proposing guidelines on improving manufacturing assembly line human-AI team performances.

1.3 Research Objective

The ongoing involvement of AI in manufacturing environments is revolutionizing the relationship between human, cyber elements, and physical environments compared to the conventional manufacturing industry. Human consideration has not advanced at the same rate as the development of AI, only highlighting technological advancement is not sufficient, given the high interconnectivity between human and AI agents in the era of Industry 4.0. Integrating human with the design and implementation of cyber-physical technology leads to the action of prompting the human-AI team to have optimal performance, thus improving manufacturing productivity. Nonetheless, little is known regarding manufacturing human operator behaviors that mainly pertain to the social perspective in CPSS. Little effort is given to seek a rigorous methodology to investigate human-AI interaction in CPSS. To fill the gap, this study aims to explore the interaction between human and AI agents in manufacturing settings. Incorporating human considerations properly can enhance the development of CPSS. The overall scope of the study is to fundamentally understand human-AI interaction from the perspective of optimizing the manufacturing productivity, thus re-construct CPSS.

The objective of the study is to develop a protocol for improving manufacturing efficiency by investigating the impact of nudge on human operators' manufacturing performances and other human factors in a manufacturing assembly line team. To do so, the concept of nudge was introduced, which can come in the form of auditory, visual, and somatic interventions, and refers to signals sent by a cyber-physical device to human operators to illicit performance-related responses. By using mixed-method approach, both quantitative data and qualitative data will be collected and used for analyses to determine if and how nudge can be observed in CPSS environments that we see today can impact human operators' manufacturing performances. In this study, we will reveal the mechanism of nudge in the manufacturing assembly line. The findings of this research will help inform engineers how CPSS should be implemented in manufacturing environments while considering the impact that CPS has on human. This research will help the manufacturing engineering community to understand how CPSS should be implemented while considering the internal interactions between human and the AI-embedded system, aiming at building a closed-loop CPSS framework for the manufacturing workplaces.

In the current manufacturing settings, AI-guided signals can be applied to manufacturing assembly lines to lead human operators to achieve better performance. Additionally, different modalities of signals may also affect human operators' manufacturing performances. Thus, nudges should be utilized as a powerful tool to investigate the underlying mechanisms of human-AI interaction. The research questions in this study are as follows shown in **Table 1**.

Table 1 Research Questions

I	Question	What impact does nudge have on human operators' manufacturing performances?
	Hypothesis	Nudge have positive impact on human operators' manufacturing performances by reducing assembly cycle time.
	Validation Approach	Through the data analysis of human operators' manufacturing cycle time.
II	Question	How do different modalities of nudges affect human operators' manufacturing performances?
	Hypothesis	Different nudge modalities have different impacts on human operators' manufacturing performances by providing with different formats of information delivery.
	Validation Approach	Through the interview data and data analysis of human operators' manufacturing cycle time.
III	Question	What are the other factors in the manufacturing environment that impact human operators' manufacturing performances?
	Hypothesis	Human operators' manufacturing performances are affected by the workplace environment and other human factors.
	Validation Approach	Through data visualization techniques to observe the underlying phenomenon.

This research employs an experimental study to investigate the impact of nudges on human operators' manufacturing performances in manufacturing assembly lines. Nudges are defined as the AI-guided intervention. By guiding human operators' perception of AI technologies, nudges are used as an instrument to test their impact on human operators' behavioral changes, presented as their manufacturing performances. Additionally, different modalities of nudges were deployed to the participants (i.e., auditory-public, somatic-private, and visual-public). It is hypothesized that AI-guided decisions in Industry 4.0, can be applied with the usage of intelligent nudge signals and that nudges impact human operators' performances in the manufacturing assembly line, the modalities of nudges can also affect human operators' manufacturing performances. Ultimately mining the phenomenon of human-AI interaction.

This dissertation unfolds as follows: We explore the foundational concepts, gaps of shape our study's design. Following this, we detail the methodology, including the design of the experiment, data collection procedures, and our approach to analysis. Subsequently, we present our results, which encompass both quantitative data and qualitative insights. We conclude by discussing the implications of our findings and proposing directions for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter provides a detailed literature background for the study, covering the transition of the manufacturing environment, advanced technology, and the human element in CPSS. This chapter also discusses the social cues in manufacturing, exploring the manufacturing research from a novel perspective.

2.1 Smart Manufacturing

Industry 4.0, the fourth industrial revolution, is a transformative concept that involves the integration of advanced technologies into the manufacturing industry. This integration enables manufacturers to automate and optimize their production processes, increase efficiency, reduce costs, and improve product quality. In recent years, Industry 4.0 has gained significant attention from researchers, policymakers, and industry leaders alike, with many studies highlighting the potential benefits and challenges associated with its implementation.

Several studies have identified the potential benefits of Industry 4.0 for the manufacturing industry. Study has shown that Industry 4.0 can help manufacturers reduce production costs, increase productivity, and improve product quality by enabling real-time monitoring and control of production processes [6], [7]. Industry 4.0 also holds potential benefits for improving supply chain management, including better inventory management, improved demand forecasting, and enhanced logistics and transportation.

However, it is identified that several challenges associated with the implementation of Industry 4.0, including the high cost of implementing new technologies, the need for skilled workforce, and concerns about data security and privacy [9]. This is of particular importance as prior research has indicated concerns with safety [12], trust [13], [14]impact on job security [7], and system security [15] within the workforce and their leadership has resulted in failed implementation. The lack of interoperability between different technologies and systems are significant challenge that could hinder the adoption of Industry 4.0. The cost of implementing Industry 4.0 technologies can be a significant barrier for many manufacturers, particularly small and medium-sized enterprises (SMEs). the cost of implementing advanced technologies prohibitively high for many SMEs, leading to a digital divide between large and small manufacturers. This can prevent smaller manufacturers from reaping the benefits of Industry 4.0 and may even lead to increased competition from larger, more technologically advanced companies. As advanced technologies become more prevalent in manufacturing, there is an increasing need for human operator with specialized skills in areas such as data analytics, programming, and robotics. The shortage of workforce with these skills could hinder the adoption of Industry 4.0 by manufacturers.

Industry 4.0 is a transformative concept that has the potential to revolutionize the manufacturing industry by enabling automation for the goal of manufacturing optimization. While Cyber-physical systems (CPS) have revolutionized the way industrial processes are being managed, monitored, and controlled. CPS combines the physical components of an industrial system with computational elements, allowing them to interact with the environment and communicate with each other. CPS has a wide range of applications in engineering manufacturing, including smart manufacturing, predictive maintenance, and supply chain optimization. CPS can be used to create smart manufacturing systems that enable real-time monitoring and control of the manufacturing process [16]. Smart manufacturing systems are capable of responding to changing conditions in real-time, leading to improved productivity, increased quality, and reduced costs. CPS can be used to monitor and control the physical components of the manufacturing process, such as machines, robots, and sensors. The computational elements of CPS can analyze the data generated by these physical components to optimize the manufacturing process. The integration of CPS with advanced technologies such as artificial intelligence and machine learning has led to the development of intelligent manufacturing systems that are capable of learning and adapting to changing conditions [17]. CPS is also applied to predictive maintenance in manufacturing systems, reducing downtime and increasing efficiency. Predictive maintenance is a proactive maintenance strategy that involves predicting when equipment failure is likely to occur based on data analysis. By monitoring the physical components of the manufacturing process, such as machines and sensors, CPS can detect potential problems before they occur. This allows for maintenance to be scheduled before a failure occurs, reducing downtime and increasing the lifespan of the equipment. The integration of CPS with advanced analytics technologies has led to the development of predictive maintenance systems that are capable of analyzing large amounts of data in real-time [18]. The supply chain is a complex system that involves the movement of raw materials, parts, and finished products from one location to another. By monitoring the physical components of the supply chain, such as inventory levels, transportation routes, and production schedules, CPS can optimize the supply chain to reduce costs and increase efficiency. The integration of CPS with advanced optimization algorithms has led to the development of supply chain optimization systems that are capable of responding to changing conditions in real-time [19].

Manufacturing has been an essential industry throughout history, and the assembly line has played a crucial role in mass production. However, traditional assembly lines have limitations, including low flexibility, high costs, and lack of integration with other systems. Industry 4.0 aims to revolutionize manufacturing by incorporating cyber-physical systems, big data, cloud computing, and the Internet of Things (IoT) to improve efficiency and flexibility. Industry 4.0 represents a significant shift in manufacturing from traditional assembly lines to more automated and efficient systems. The integration of CPS, AI, IoT, and cloud computing has revolutionized the manufacturing process, making it more efficient, flexible, and cost-effective. The collaboration paradigm has shifted from machine-centric to human-centric, with machines communicating and cooperating with each other. This has resulted in a significant reduction in lead time, increased productivity, and lower production costs.

The traditional assembly line is a sequential process where human assemble products in a linear fashion. Human workers are responsible for specific tasks, and the products move from one station to another until the final product is complete. The traditional assembly line has some limitations that hinder its efficiency, such as low flexibility, high costs, and low productivity. Moreover, traditional assembly lines heavily rely on human labor, making it prone to human error and causing long lead times and high costs. The traditional assembly line has been the backbone of manufacturing for over a century, relying on a fixed sequence of human-operated stations. The Industrial Revolution brought about the use of assembly lines to produce goods on a mass scale.

With advancements in AI and automation, the manufacturing industry has undergone a transformation towards Industry 4.0, where the assembly line now involves more AI than ever before. The Industry 4.0 assembly line incorporates cyber-physical systems, IoT, and AI to increase efficiency and flexibility. The Industry 4.0 assembly line is more automated, and machines can communicate and cooperate with each other, creating a more efficient system. With Industry 4.0, there is a significant reduction in lead time, and production costs are significantly reduced. In a traditional assembly line, human perform repetitive and manual tasks, requiring physical dexterity and accuracy. These tasks can be time-consuming and often result in human fatigue and injuries. On the other hand, the AI-involved assembly line involves robots, sensors, and machine learning algorithms, which can work with greater accuracy and speed. AI technology has revolutionized the manufacturing process by replacing human with intelligent machines that can complete tasks faster and more efficiently. For example, in the automotive industry, robots equipped with cameras and sensors can inspect every car part and identify defects with high precision, which is not possible with human inspection. In traditional assembly lines, human are responsible for quality control, which is a significant challenge as it involves detecting and correcting errors in real-time. In contrast, in the AI-involved assembly line, quality control is more accurate and efficient as it uses machine learning algorithms that learn from past errors and identify problems quickly. Furthermore, AI can analyze vast amounts of data generated during the manufacturing process and provide insights that can help optimize the production process. This can lead to reduced costs, increased productivity, and improved product quality. The collaboration paradigm has also shifted with the adoption of AI technology. In a traditional assembly line, human are responsible for a specific task and perform it repeatedly throughout the production process. However, in the AI-involved assembly line, human must collaborate with robots and machines to complete tasks. Human operators must be trained to operate and maintain machines and robots, and the interaction between humans and machines must be seamless to ensure that the production process is efficient and effective. Moreover, the introduction of AI technology has led to the creation of new job roles in the manufacturing industry. As machines and robots replace repetitive manual tasks, human operators are required to acquire new skills such as programming, data analysis, and maintenance. In addition, AI technology has increased the demand for engineers and technicians who specialize in the development and maintenance of automation systems.

The comparison between traditional manufacturing assembly line and the current AI-involved assembly line has shown that AI technology has revolutionized the manufacturing industry by improving the speed, accuracy, and efficiency of the production process. AI technology has also led to changes in the collaboration paradigm, requiring human to collaborate with machines and robots, and acquire new skills. Although the adoption of AI technology has led to the displacement of some workforce, it has also created new job roles and opportunities. As technology continues to evolve, the manufacturing industry will continue to transform towards Industry 4.0, and the role of AI in manufacturing will become even more significant. Manufacturing performance is an essential part of the manufacturing industry. The performance of a manufacturing process is determined by its productivity, quality, cost, and flexibility. Improving manufacturing performance is critical for industries to remain competitive in today's rapidly changing environment. With the advancement of technology, manufacturing processes have become more complex, and the collaboration between humans and machines has become more critical. Therefore, it is necessary to study manufacturing performance to ensure that the human-AI collaboration in the current manufacturing assembly line is optimized.

The need to focus on improving human-AI collaboration in the current manufacturing assembly line is due to the fact that technology is advancing at a rapid pace, but human development is not keeping up with the same rate. As a result, there is a widening gap between the capabilities of machines and the capabilities of humans. The integration of AI in manufacturing processes has resulted in the creation of a new type of manufacturing environment, where humans and machines work together. These environments require the development of new skills and expertise to ensure that the collaboration between humans and machines is optimized.

The study of manufacturing performance can help industries to identify areas of improvement in their manufacturing processes. By analyzing the performance data of a manufacturing process, industries can identify the bottlenecks in their processes and take necessary steps to optimize them. For instance, the analysis of the performance data can help in identifying the parts of the process where human error occurs, and take steps to mitigate them. Similarly, the analysis of performance data can help in identifying the areas where machines can take over repetitive and dangerous tasks, which can free up human for more complex and creative tasks. One of the key benefits of studying manufacturing performance is that it can help industries to optimize their manufacturing processes. By optimizing the manufacturing process, industries can reduce their costs and increase their productivity. For instance, the optimization of a manufacturing process can lead to a reduction in the time required to produce a product, which can result in cost savings. Similarly, the optimization of a manufacturing process can lead to an increase in the quality of the product, which can result in increased customer satisfaction. The study of manufacturing performance can also help industries to ensure that their manufacturing processes are flexible. Flexibility in manufacturing processes refers to the ability to adapt to changes in demand or product design [20], [21], [22], [23]. The ability to be flexible is critical for industries to remain competitive in today's rapidly changing environment. By studying manufacturing performance, industries can identify areas where they can improve their flexibility [20], [24], [25], [26], [27], [28]. For instance, the analysis of performance data can help in identifying the parts of the process where changes in product design [29] can be made without affecting the overall production process [30], [31], [32], [33], [34], [35]. Study on manufacturing performance is essential for the manufacturing industry. With the rapid advancement of technology, the collaboration between humans and machines has become more critical. Therefore, the need to optimize the collaboration between humans and machines is necessary to ensure that the manufacturing process is efficient and effective. The study of manufacturing performance can help industries to optimize their manufacturing processes and ensure that their manufacturing processes are flexible.

The manufacturing industry is still undergoing significant transformations, from the traditional assembly line to today's digital age. Smart manufacturing refers to the integration of Industry 4.0 advanced technologies to optimize production processes, reduce costs, and improve product quality. Traditional manufacturing is more inclined to a production format where goods are produced in a repetitive and sequential process.

Repetitive tasks and manual labor are involved, and what's more, it relies on human decision-making and expertise. Traditional manufacturing is labor-intensive, time-consuming, and prone to cause more errors, which can lead to inefficiencies and low productivity. Moreover, traditional manufacturing is not responsive to changes in market demands, making it difficult to adapt to new trends and consumer preferences. The emergence of digital technologies has provided the manufacturing industry with new opportunities. Smart manufacturing is a response to these needs, integrating advanced technologies to transform the manufacturing process. The goal is to make manufacturing more efficient, cost-effective, and responsive to market demands. Smart manufacturing involves the use of advanced technologies such as IoT, cloud computing, big data analytics, and AI to optimize the production process. These technologies enable real-time data collection, analysis, and decision-making, making the manufacturing process more efficient and cost-effective.

Computational models can learn from data, and the algorithms enable them to make decisions and perform tasks that were previously done by humans. AI-embedded machines can optimize the production process, reducing errors and improving efficiency. By integrating advanced technologies, the traditional manufacturing environment has now transformed into the present smart manufacturing environment. The integration of advanced technologies such as IoT, cloud computing, big data analytics, and AI brings several benefits to the manufacturing industry, including improved efficiency, reduced costs, and improved product quality, which boosted the development of manufacturing industry.

2.2 Cyber-Physical-Social System

CPSS refers to the cyber-physical-social system, which extended the development of CPS. CPSS integrates the social space into advancing the development of prior CPS, forming a bigger ecosystem by paying more attention from the social perspective. CPSS integrates three elements, keeping them in a dynamic loop, and the relationships between the cyber, the physical, and the social elements are reconstructed over time [36]. The notion of CPSS is derived from CPS and cyber-social systems (CSS), which serve as a platform for computational performances [37]. CPS and CSS converged into CPSS to benefit the interactions among cyber, physical, and social elements as they are closely connected. The advantages of shifting our attention to build a stronger CPSS can be explained in two perspectives. First, the cyber, physical, and social elements are bonded tightly within CPSS, thus CPSS can be embedded in different contexts under circumstances where there are specific demands [37]. Second, for combining CPS and CSS, CPSS have higher adaptability compared to either conventional system (CPS and CSS), for it can tackle tasks arising from cyber, physical, and human elements by providing integrated computing tools [38]. The emergence of high-frequency interaction between human and IoT environments brought attention to the transition from traditional CPS to CPSS. The revolution towards an integrated CPSS is still at its beginning, existing methods can only test small-scale CPS, it is critical to forming a homogeneous method to examine CPSS.

Common computational tools used in CPSS are essentially designed for tracking the interactions between human, society, and the physical elements, which emphasizes the relationship between those three components. Actions need to be taken on developing technology computing mechanisms to fortify the foundation of CPSS design. CPSS is essentially designed for tracking the interactions between human, society, and the physical elements, which emphasizes the relationship between those three components and aims to provide a platform focused on human response to cyber and physical counterparts. The role of human in CPSS is of great difference compared to conventional systems where only human considerations are involved [37]. It is important to investigate a CPSS framework as a human-centric system to facilitate manufacturing efficiency in synthetic environments, which will have profound significance to engineering workforce performance. CPSS evolves with the human-AI interaction and thus, understanding how technology affects human behavior and cognition is indispensable in developing a CPSS. Human considerations lead the research to a cognitive, ethical, and educational perspective, where the concept of "nudge" should be brought in. Nudge theory is useful in that it elaborates how the non-linear human decision-making process is affected and evolved by external factors. The figure below shows the evolution from CPS to CPSS.

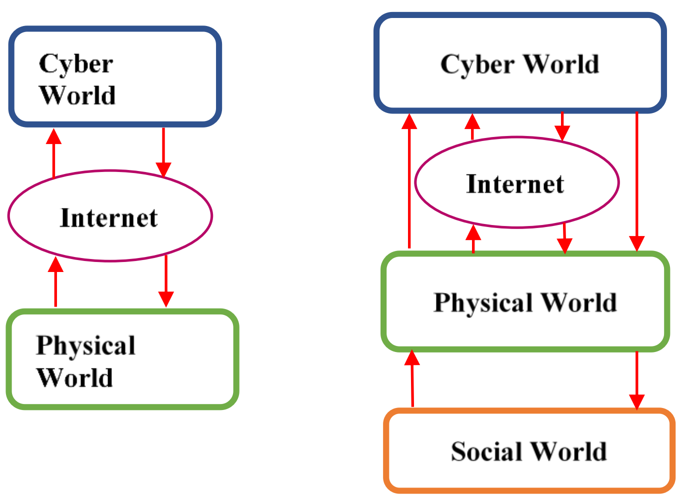


Figure 1 Comparison between CPS and CPSS

Industry 4.0 has changed the manufacturing sector into a smart environment, where CPS plays an important factor in this transformation. Industry 4.0 is predominately led by the advancement of CPS and advancements in Information and Communication Technologies (ICT) [39]. These developments facilitate a huge amount of digital transformation by providing connectivity and sophisticated computation, and those led to the production systems coordination promotion and achieved the goals of factory implementation. Industry 4.0 provides the future digitalized industrial environment with potential solutions, and the impact of Industry 4.0 is noticeable in manufacturing and automation industries. One of the most anticipated results is the assignment of laborious and repetitive work to intelligent machines and robots [40], [41]. Previous research found out the design method that majorly involves the coordination of the physical machine and phenomena in the computational analysis [42], The digital transformation age is developing quicker than anticipated. One element in this transformation is the enhancement of dynamic and complex collaboration mechanisms in industries, notably human-machine cooperation [43], [44], [45], [46].

In many industrial situations, the nature of human and CPS linkages necessitates cognitive engagement in addition to job performance. However, existing methods to the design of industrial systems mainly depend on the basic notion of CPS, which lacks the consideration of socio-technical implications in designing the system, this can decrease cooperation quality and may affect safety [47], resulting in problems to supply and adapt to the rapid expansion of Industry 4.0. People often do not adhere to regulations that do not correspond to their way of thinking, preferences, needs, and talents. In addition, each person is unique, and individual behavior under varying conditions is driven by complicated phenomenon that has not yet been completely understood. As Industry 4.0 enhances such collaborative industrial settings, a design framework that extends beyond CPS is needed. Thus, a system design process that considers human elements will be an essential element of the future digitalized industrial environment.

The concept of CPSS is still at its infant, it is created by introducing a social element into the CPS. CPS and social system are the components of CPSS from a holistic standpoint. CPS refers to a generation of systems with combined computational and capabilities that have close links to Industry 4.0 [48]. The social element refers to human who interact [49], [50]. The previous system has transferred into a hyper-connected industrial ecosystem as a result of developments of manufacturing automation, which not only enables smart production but also organizational integration in real-life industry sectors. Thus, actions are needed on the development of cooperative, networked, and intelligent industries. The development of manufacturing settings where human closely cooperate with sensor-enabled smart equipment and robots is one of the rising trends in the digital transformation of industries. Because human factors are not taken into consideration in CPS design frameworks, human engagement in such smart settings presents particular issues for system-built approaches. This is how the knowledge is produced in the context of Industry 4.0 and CPSS manufacturing settings.

2.3 Human-AI Interaction and Teaming

Recent years the field of human-AI interaction has been growing rapidly. HAI explores the ways of how human agents and AI systems can interact with each other. As Industry 4.0 shifted the manufacturing industry significantly, HAI has the potential to achieve the goa of manufacturing optimization by enabling AI systems to work alongside human workers. By using AI-enabled systems in the manufacturing plants, human worker can get rid of the laborious and repetitive tasks for the AI-embedded physical machines can assist with them, and those AI systems can also help boosting the efficiency for computational algorithms are able to generate accurate results. In addition, AI systems can process vast amounts of data in real-time, providing human workers with insights that would be difficult to obtain. This can help to improve overall performance for helping with decision-making processes.

HAI has been widely applied in manufacturing for the purpose of predictive maintenance systems. Computational algorithms are used in the predictive maintenance systems to analyze data from physical machines and other equipment, to predict when maintenance will be needed. This can help achieve the goal of reducing manufacturing downtime and improving overall equipment effectiveness. Research found that the efficient HAI in manufacturing have great impact on manufacturing optimization. HAI helps to improve the accuracy of quality control inspections and reduce the likelihood of defective products reaching customers. The use of AI-assisted quality control systems in manufacturing can improve product quality and reduce costs. HAI has gained increasing focus from the manufacturing industry, as AI systems continue to play a larger role in the manufacturing process. Manufacturing companies can retrofit their factories by adding industry 4.0 technologies. The current use of collaborative robots, predictive maintenance systems, AI-assisted quality control systems, and AI-assisted process optimization systems are all critical to improving overall manufacturing performance. As AI technology continues to evolve, it is likely that HAI will continue to play an important factor in the manufacturing industry renovation.

The relationship between human and AI is explored from different perspectives with the expectedly prevalent use of human-AI interaction in the manufacturing workplaces in Industry 4.0. One of the perspectives is from team research [51], [52]. Human-AI teams, which are often used interchangeably with the term human-autonomy teams (HATs), drives the tension in Industry 4.0 applications as a wide spectrum of factors including various elements such as humans, processes, and technology contributes to the complexity of human-AI interaction with the possible management tension [53], [54], [55]. The tension arises from the interdependence between automation (i.e., delegating human input to artificial intelligence) and augmentation (i.e., following AI-directed guidance in performing a task) [53]. The tension also relates to the trust issue in human-AI teams–how human can form a trusting relationship with artificial intelligence in following their guidance [5], [56], [57], [58]. In the field of human-AI interaction, human-AI team dynamics are also acknowledged to be investigated, which is closely tied to the agency [59], mental models [60], teaming processes and overall team effectiveness [51].

Human-AI teaming refers to any work process wherein human agents work interdependently with autonomous agents with agential capacity towards a common goal [51]. Autonomous agents indicate any computational intelligence with properties of self-governing and self-directedness [51]. In either scenario of automation, wherein autonomous agents take over the whole decision-making process, or augmentation, wherein human input is necessary to complete the whole task [53], AI plays a predominant role as an autonomous agent. Particularly in the Industry 4.0 context, AI solves industrial problems and adapts to environmental changes with its predictive capacity [61]. In modern manufacturing plants, AI-embedded system has been widely applied to augment human worker performance. That is, in the manufacturing environment in Industry 4.0, AI is considered a supportive or enabling system for human workers to achieve better manufacturing performances in industrial processes.

With the perceived importance of AI's supportive or enabling role in assisting human workers' performances in Industry 4.0, how to lead human workers' decision-making in a good direction becomes an important question. Optimizing human involvement in decision-making processes is one of the key concerns in designing human-AI teams in Industry 4.0 [61]. In the condition of the AI-advised decision-making process, human performance shows a significant increase in an ideal combination of artificial intelligence and human input. However, the contribution of AI to team performance depends on the domain and types of interaction design, giving prominence to the research on the complex dynamics of teams [55].

Several types of research offered interdisciplinary insights into the complexity of human-AI teaming. Human-AI interaction originated from diverse disciplines, including team formulation [51], [52], [60], efficiency [53], and ethical perspective [56], [59]. The commonality of the diverse perspectives is their highlight on trust building. To promote human-AI team performances, trust-building becomes a key issue as human tend to build trust more when they have a clear sense of the whole decision-making process, including AI's roles and responsibilities throughout the working process [39], [60]. From the team efficiency perspective, working with AI creates a new paradoxical tension as the designation of decision-making is not simple. AI-inspired solutions in the future of work will produce a feasible scenario that sits in between the spectrum with two ends of automation (a complete delegation of decision-making power) and augmentation (an intervention of human autonomy with the assistance of artificial intelligence) [53]. Humans delegate their decision-making roles. This indicates that human in the feedback loop needs more explainable AI to recognize and understand the mechanism behind the solutions and make the AI-inspired decision more transparent and reliable [62]. Humans delegate their decision-making role to artificial intelligence on either pragmatic grounds that AI will enhance the general well-being of individuals or epistemic grounds that it is rational to believe that AI is trustworthy [56]. Trust, in the human-AI interface, is incremental rather than exponential; that is, our trust in AI's contribution to our well-being depends on the context of the relationships, and emerges organically over the period. Therefore, the concept of nudge is pulled in and serves as an instrument in discussing trust in human-AI interaction.

The effects that an individual's self-perception has on their performance in a task has been a topic of study for decades, such as the relationship between attitudes/beliefs and behaviors [25]. The different factors that make up an individual's perception of their abilities or experience, such as confidence levels [63], can affect various performance metrics when performing an assigned task. These factors can be considered in a multitude of fields, such as the effects of academic competence on academic performance [26], or performance metrics in engineering environments such as manufacturing. Individuals in the field of engineering identify and find an affinity for different features of a domain [27], and these differing affinities can influence competency and behavior when performing tasks in manufacturing environments. As a result, it is critical to consider a “perception-reality gap” as a factor that affects workplace performance, as well as have the ability to identify and analyze this gap.

2.4 Smart Nudges

Nudge refers to steering individuals’ decisions towards desired outcomes by intentionally structuring the choice architecture [64], [65]. The idea is to direct choices in a certain direction without intervening human’s freedom of choice. Here, nudges are not obligatory, for the essence of nudge do not mandate or force human to make choices, they function as a trigger to alter human’s choice architecture, and initially facilitate decisions that can benefit the individual. Initially, a nudge was defined as any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. For example, for displaying the food at customers’ eye levels can encourage the customers be more likely to choose those products. Furthermore, nudges can come in different forms, including changes in how information can be presented. The fundamental function of how nudge works is that it can change human behavior but also maintaining freedom of choice in the meantime. Nudge theory recognizes that human beings do not always act rationally. Human often make rational choices by continuously comparing multiple options and their choices [66], they are expected to make irrational choices, However, nudge theory posits that people often act irrationally, necessitating that choice environments take this into account. Nudges subtly guide decision-making by highlighting specific options while still offering a wide range of choices. Nudge theory tackles the complexity of balancing free choice with beneficial outcomes, subtly steering individuals towards optimal decisions without overtly restricting their options. In practice, nudges might appear as comparative feedback on utility consumption, or by increasing the visibility and accessibility of healthier food options. [67] [68] [69]. The idea of nudging is of significance for understanding the manufacturing engineering from a social perspective, especially understanding the context of human-AI interaction within CPSS. Using the nudge strategy can help comprehending how the technologies can shape human behavior and cognition and how to implement the design of them in the future. Research highlights how corporate influence can be embedded in choice architecture to serve their interests, as illustrated in how digital platforms influencing human choices[70] [71]. It is anticipated that integrating nudge principles into CPSS will promote the development of engineering workforce training.

CPSS integrates physical processes, computational resources, and social interactions to create a more intelligent and adaptive ecosystem. Nudges in CPSS can improve the system performance by steering the human decision-making process and changing their behavior. CPSS takes data from physical machines using advanced algorithms and provides real-time feedback by analyzing the big data. Nudges were applied in CPSS through information-aware formats, providing timely and context-specific reminders to human users for task purposes. For instance, human workers who work at manufacturing plants might receive a reminder to take a break if they have been working for a long period of time without rest. Real-time feedback and reward systems can enhance human performance for leading desirable behaviors, such as workers receiving feedback on their productivity and being rewarded for meeting or exceeding targets. Social norms also emphasize the social environment’s impact on human, such as showing information about the energy consumption of similar households to nudge individuals to reduce their energy use. Personalization can tailor nudges to individual preferences and behaviors, with CPSS analyzing data to understand users' habits and adjusting the design nudges accordingly, such as personalized notifications reminding individuals to behave in a desired way.

In the context of the online and digital platforms, nudges within these systems illustrate how information frameworks can subtly influence users' actions in the ways that most users are not even aware of. For example, digital nudges can be observed when platforms guide users through notifications or prompt them to confirm their intention to log off before ending their session [72], [73]. The subtle impact of digital nudges lies in their timing and diverse formats, including text messages, push notifications, vibrations, or ringtones. In the realm of human-AI interaction, nudges reflect designers' aims to create feedback loops that encourage choices believed to benefit human users. A crucial aspect of crafting choice environments for nudging is ensuring that it neither forces the desired choice nor restricts other options. [74].

Integrating nudges into manufacturing assembly lines within CPSS can significantly enhance performance and efficiency. Nudges can enhance productivity by reminding workers of their progress and encouraging them to stay on task, such as visual cues on screens or wearable devices alerting workers if they are having a relatively slow work pace in the team. They can improve safety by reminding workers to wear protective protection, follow safety protocols, and take breaks to prevent employee fatigue, by developing sensors to detect if human employee is not wearing safety protection and the sensor equipment will send an alert based on the detection. Nudges can also help improve energy efficiency by encouraging energy-saving behaviors, such as physical machines being programmed to switch to low-power modes when not in use and workers receiving prompts to turn off equipment that is not needed. By alerting human workers if a product does not meet quality specifications, quality assurance could be achieved by prompting human workers to fix errors. It is of great importance that effective communication in assembly lines, and the engagement of nudges can facilitate better teamwork communication by providing critical information and notifications. By providing timely reminders and feedback, nudges can reduce stress and cognitive load on workers, leading to a more positive work environment and lower turnover rates, thus benefiting human well-beings.

There exist a lot of applications of nudges in the CPSS environment, including Amazon using an ultrasonic wristband that has built-in algorithms to track the productivity of workers in its fulfillment centers, where employees get nudge signals to maintain a certain work pace, and deviations trigger alerts and feedback, maximizing efficiency while ensuring workers are aware of their performance in real-time. In other smart factories, nudges are used to guide human through complex assembly processes, with augmented reality (AR) glasses providing step-by-step instructions and highlighting areas that require attention, those are considered visual nudges, and can help reduce errors and increase working efficiency. Manufacturing plants that are equipped with energy management systems can use nudges to encourage energy-saving practices, such as workers receiving notifications about energy consumption patterns and suggestions for reducing usage during peak hours. Nudges can also enhance compliance with safety protocols, with wearable devices monitoring workers' physical conditions and sending alerts if they detect signs of stress, reminding human workers to take necessary breaks.

While nudges offer significant benefits, challenges and considerations do remain. The use of data in the design of nudges brought attention to privacy, data collection and usage should be transparent and respect individuals' privacy. Furthermore, nudges should be adjustable to be able to adapt to different contexts and individual preferences, as a one-size-fits-all approach may not be effective, as customization is crucial for designing nudge technologies with higher accuracy based on different contexts. The impact of nudges should be continuously measured and evaluated to ensure they are achieving the desired outcomes, requiring robust data analytics and feedback mechanisms.

Between the human and AI interfaces, nudging signifies a deliberate effort by designers to establish a feedback loop that encourages a particular choice, believed to be advantageous for users [75]. A key tenet in designing a choice architecture for nudging is to avoid both compelling the preferred choice and prohibiting other alternatives [64]. Nudges have been identified as effective in aiding users to make more beneficial decisions for themselves in practical applications, such as opting for more secure networks or refraining from posting certain information on social media.[76] [77].

The effectiveness of nudges in helping users make better decisions has been well-documented in real-world contexts like choosing safer networks or not sharing specific information online. The intention of the system designer is pivotal when crafting nudges. Some research has underscored the necessity of understanding the potentially coercive nature of nudging, particularly when integrated with big data technologies.[78]. Nudges powered by big data can easily influence public opinion toward specific agendas. To address concerns about nudges becoming coercive, it is essential to ensure transparency

[79] [80]. This involves creating a nudge environment that is inclusive, explainable, and trustworthy.

The involvement of nudge in CPSS holds great significance. In manufacturing environments, an effective nudge cue should assist workers in making desired decisions, thereby improving production performance. The development of AI, machine learning, and IoT provides the manufacturing industry with faster, more powerful tools for analyzing data, providing real-time feedback, and ultimately managing organizational operations. These technologies should also be designed to assist humans in making better decisions and enable a positive workplace by enhancing human well-being. Research should continue to investigate the most effective ways to implement nudges in various contexts, how to combine nudge theory with advanced technologies to better assist human operators, and the long-term effects of nudges on human behavior and well-being. The incorporation of nudge technology can provide an effective strategy for optimizing manufacturing assembly line outcomes. By integrating nudges into manufacturing, goals can be achieved in creating a more sophisticated, dynamic, and harmonious CPSS environment. For most manufacturing plants, higher efficiency, greater productivity, and improved human operator performance can be attained. Thus, by using the nudge-involved CPSS framework, larger ecosystems can be revitalized. As factories transition into smart factories, the nudge strategy can help small enterprises evolve from small-scale operations into larger, integrated smart systems.

2.5 Social Cues

Social cues are crucial components in the manufacturing context, because of the involvement of human operators. Social cues are signals and indicators that are derived from the environment and human would have interactions within it. Social cues can significantly affect human perception, behavior, and thus the performance of individuals. In manufacturing assembly lines, social cues are generated from various resources such as workplace layouts, coworkers' behavior, the communication between human operators and the physical machine, and interaction between human operators and the manufacturing organizational culture.

Social cues are the subtle signals that help individual human operator to understand the social environments and interact with their social environments. In the context of manufacturing assembly lines, social cues can be represented in the form of non-verbal information, such as body language, people's facial expressions, and even the spatial layout of the workspace setting. For human operators, detecting and comprehending social cues reasonably is crucial for manufacturing team communication, and collaboration. Visual cues for instance, the piling up in the buffer zone between the workstations can signify the abnormal workflow, while the empty buffer zone might indicate the workflow of the team is smooth. Auditory cues in the workplace environment include sounds that can signal different situations; for example, an abrupt noise may indicate an emergency. Operational research highlights that the spatial arrangement of a workplace is a crucial component of social cues. For instance, the proximity of human operators to one another can significantly impact team communication and collaboration. Environmental social cues can also reflect the organization's level of organization. A well-designed, positive workplace setting can enhance productivity, while a poorly designed environment can cause stress for human operators, leading to counterproductive outcomes.

Social cues play a significant role in how human operators perceive workplace information and ultimately determine their behavior. It's important for organizations to design manufacturing assembly settings to ensure that social cues are positive and assist human operators rather than adding cognitive load. Positive social cues can lead to effective communication and team coordination, facilitating the smooth operation of the assembly line. For example, eye contact helps human operators understand the engagement of their coworkers. If a coworker maintains eye contact, it indicates that they are following instructions. Conversely, the lack of social cues may suggest a lack of attention or a need for further clarification. Positive social interactions can foster trust and cohesion among team members, leading to higher productivity in the organization.

Trust is an important factor in shaping human perception, whether it is trust in humans or AI systems. Trust determines the level of human agency towards an object and can be a key factor in the decision-making process. Building a positive manufacturing assembly environment can greatly influence human well-being. A positive workplace will have positive social cues, reduce stress levels, maintain normal workflow, and lead to optimal team collaboration. On the other hand, a negative workplace environment can result in poor team collaboration. The lack of social interactions or misunderstanding of social cues may cause job dissatisfaction, add cognitive load, and lead to health issues.

Social cues can also directly influence the manufacturing team's efficiency and productivity. Positive communication can lead to a better understanding of tasks and can foster quicker resolution of problems, thereby enhancing organizational productivity. For example, positive reinforcement can motivate operators to perform. The physical and social environment of an assembly line can shape how operators perceive their work and interact with each other. The design and layout of the assembly line can facilitate or hinder social interactions. For instance, a well-designed assembly line allows human operators to communicate with their coworkers easily, have quick access to machines, and thus promotes efficiency. Conversely, a poorly designed assembly line, such as one with many physical barriers that force operators to take alternate routes to access machines, can cause frustration and lead to performance deficiencies. Organizations should emphasize facility design for optimal operations and communication. Organizations that value employees' well-being and focus on creating a positive workplace environment always succeed. The reason why social norms are important is that they can shape team interaction and group dynamics on the assembly line. A manufacturing assembly line consists of many parts, each of which must coordinate with the others to ensure a smooth workflow. Social norms are crucial in shaping human behavior; positive social norms can foster support and timely assistance within the group, while negative social norms can cause misunderstandings in team collaboration, leading to decreased manufacturing performance.

CHAPTER 3

METHODOLOGY

The purpose of this chapter is to present the details of the experiment design, data collection, and data analysis methods. We first propose the research framework, then delve into the protocol study, and finally talk about what methods we used to analyze the results.

3.1 Research Framework

This study proposed a research design framework that tests if any, how nudge works in the CPSS setting. The research was executed by taking a real experiment approach to investigate the impact of nudges on human operators' responses. The experiment is designed to simulate the experience of nudges by an algorithm in a manufacturing setting. Quantitative and qualitative data will be collected to determine how nudge impacts human operators' manufacturing performances.

In addition, we will explore how different types of nudges (auditory, visual, and somatic), the recipient of the nudge (individual or group-wide), the privacy of nudges (if the nudge is private to the recipient or if it is public), and the human operators' perceived performances of the assembly tasks (through observable work in progress) will impact their responsiveness to nudges. We hypothesize perceptions of nudges can affect manufacturing performance to some extent, depending on different individuals. Embedding the concept of nudging into CPSS will prompt the development of engineering workforce training. Future work is to investigate how to increase positive impact by using nudge signals to implement human-AI interaction. This research elaborates on the design of the experiment which will benefit the scientific community by introducing the integrative research framework that explores the human response in human-AI interaction. As CPSS is still in its infancy, a unified model framework that can be widely applied to examine the system is yet to be realized.

This research starts the conversation on CPSS within manufacturing environments and the considerations that are needed. Further, the research considers the gaps, their formulation into research questions, and the impact they will have on implementation and practice. A summary of the gaps, research questions, and potential impact are shown in **Table 2** below.

Table 2 Summary of Gaps, Research Questions, and Impact

Gaps	**Research Questions**	**Potential Impact**
There is minimal fundamental understand on human response to nudges in CPSS environments.	RQ1: What impact contribute to the impact of nudges on human operators' manufacturing performances?	Provides foundational knowledge on human acceptance of nudge in CPSS settings.
Different modalities of nudges have a host of different implications that could impact human acceptance and response to nudge. This relationship is currently not understood.	RQ2: How do different modalities of nudge impact human operators' manufacturing performances?	Informs how nudges should be implemented in manufacturing environments to increase likelihood of positive human behavior in response.
Nudge is designed to shift human behavior. However, there are factors in the social environment that may conflict with those given by the nudge. How a human reconciles those countering cues is not understood.	RQ3: How do human operators perceive the AI-nudging experience ?	Provides information on how human prioritize and response to nudge when conflicting information is provided.

Cultivating the methodological analysis of CPSS is intricate, for the analysis can start from multidimensional directions. In this case, component-based methodology affords the guidance. The cyber, physical, and social elements hold relatively equivalent roles in component-based methodology. The dynamic interactions among these three components can have different functionality in variable settings, components interact with each other. Further, another advantage of involving component-based methodology is that, when encountering changes that cause negative effects, the component model has a strong adaptability of embracing error without affecting the overall growth of the system [37]. Under situations where there are conflicts, a study has been performed on the flexibility of the component-based model for choosing partial interactions in the system and making the correct determinations [81].

We aim to develop a protocol for the cyber-physical-social system. We used the protocol analysis here as the experiment we designed follows a problem-solving process, where the nature of protocol analysis is to study information processing [82]. The core of information processing theory is that human behavior (reaction) is the product of information processing through human brains and since human thoughts are invisible, human behavior is considered as a resource for research analysis [83].

As shown in **Figure 2**, The proposed experiment involves the observation of human response to nudging. Pre-experiment instructional treatments utilized are lecture-based approach (lecture-based method) and inquiry-based approach (inquiry-based method). The lecture-based method is a traditional teaching model, where information is delivered in the format of lecture verbally by the instructor, usually along with the assistance of external tools (i.e. physical tool-chalkboard, technological tool-projector) [84]. This method is efficient for allowing the delivery of information (knowledge, instructions) in a well-planned manner, clearly and controllably.

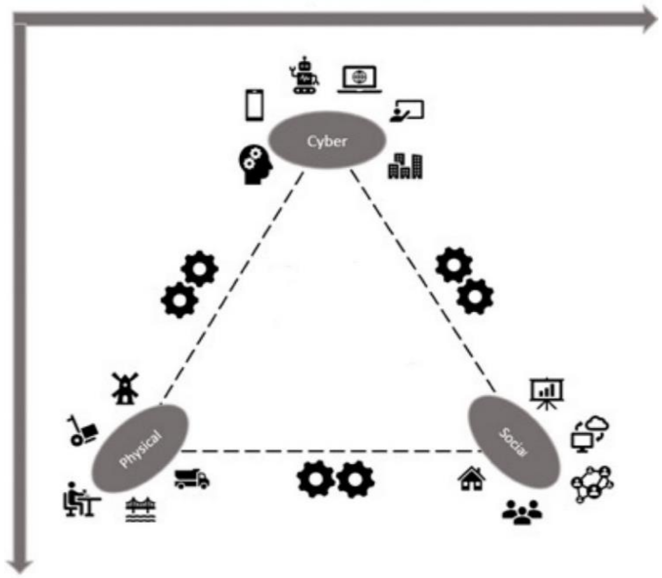


Figure 2 Navigation Towards a Unified CPSS Model

The inquiry-based method is a user-centered method where users are guided through prompt questions, and problem solutions, and results are generated by users. Users are highly engaged in this method and thus can build intimate connections with what they learn. By generating pre-experiment methods in protocol study, the proposed experiment we designed investigates two main actors of CPSS: human operators (i.e., system developers & system operators) as well as AI elements (i.e., algorithm & robots) through the exploration of their interactions.

3.2 Experimental Study

We devised an experimental setup to investigate the interaction between human and AI in a simulated manufacturing environment. Participants were asked to engage in assembly line tasks and were informed they would receive AI-generated nudges to enhance their manufacturing performance, except for the control group. We intentionally misinformed participants that nudges are AI-originated while human researchers coded them. The deception layer was embedded in the research design to control participants' prior knowledge regarding AI technology, which reduces uncertainty emerging out of the human-AI interaction and affects the research. We scheduled nudges at specific intervals during the experiment for all the participants, each person received an equal number of nudges. Each team is formed of three engineering students to simulate the interdependent work patterns of employees in the manufacturing assembly line workplaces. Students were recruited from four engineering majors, which are mechanical engineering, electrical engineering, computer engineering, and civil engineering. For engineering students in those majors, the curriculum typically includes some hands-on projects that improve their familiarity with mechanical systems and experience in manufacturing and fabrication. This ensures that the study results are not influenced by the participant's lack of knowledge about these systems. Students signed a consent form indicating their willingness to participate. Each student got a compensation of a $50 Amazon gift card.

30 engineering major students were recruited as assembly line operators and the experiment was carried out in a university laboratory setting. Within each group, students randomly pick one workstation among the three. Participants were divided into ten groups, 9 test groups (where participants were nudged) and one control group (where participants were not nudged) for comparison. Each group comprised three participants and was assigned to conduct a simple interdependent group task of assembling a hand-held power tool.

Each group member is required to complete an independent assembly task (finish assembling the preset number of parts), and each group is assigned to conduct a simple interdependent group task of assembling a hand-held tool. Students conducted individual tasks on the table. Institutional Review Boards (IRB) was approved to ensure the welfare of participants involved in this experiment. Researchers controlled the manipulation of independent variables. The buffer zones between workstations are used to place the finished parts. Upon completion of the individual assigned portion, the power tool is passed on to the next person. The assembly line setting is shown in **Figure** .

Figure 3 Experiment Assembly Line Setting

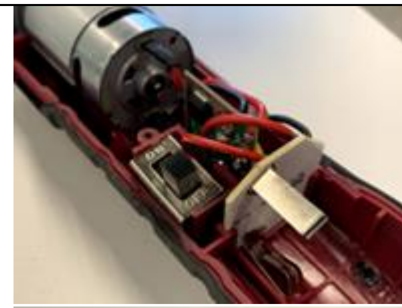
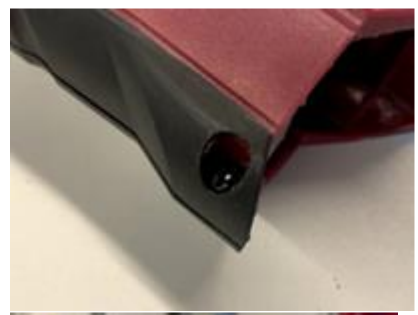
The manufacturing assembly line task involved the sequential assembling of the hand-held power tool through all the workstations. The assigned task in this study is the manufacturing assembly of a 12-volt lithium-ion oscillating multifunction power tool, as shown in **Figure 4**.This power tool contains 37 parts (blades and battery removed) and requires 19 assembly steps. The total assembly time for the component varies from 20-30 minutes. The power tool includes a sharp blade and battery that are removed from the assembly process for safety purposes. The assembly line is designed as an imbalanced line with three workstations. The assembly steps are divided into three workstations (refer to as cells) where the divisions of steps are designed to control Work in Progress (WIP) between cells.

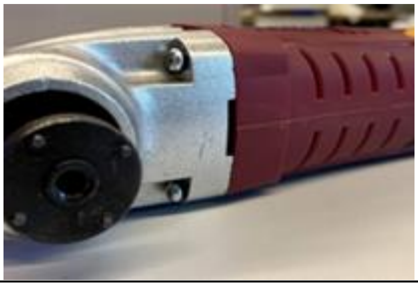
Figure 4 Chicago Electric Brand Oscillating Multifunction Power Tool

The assembly line is intentionally designed with imbalances for several reasons. One reason is to optimize production efficiency by allocating tasks according to specific requirements of the assembly processes. By assigning different workloads to different workstations, imbalanced assembly line design considers the specific equipment requirements (additionally, specialized expertise in real manufacturing plants). More importantly, an imbalanced assembly line allows for flexible production rates and capacity adjustments. Each of the three participants worked on their respective workstation's assembly tasks. **Table 3** below is an example of individual assembly tasks for workstation A, B and C.

Table 3 Assembly Tasks for Individual Workstations

Workstation A Picture instruction	Word instruction	
	1) Insert the rocker (Bin 1A) into the silver head (Bin 1B). 2) Screw the black bolt (Bin 1C) into the silver head and through the rocker by hand. Tighten the rest of the way with the wrench.	
	3) Align the motor (Bin 2A) to the silver head with the black motor wire on the left. 4) Insert one screw (Bin 2B) in each of the two guide holes. *Thread By 1 Turn	
	5) Screw in the screws on the motor 1) Insert a rubber stop (Bin 3A) into the appropriate location within the casing (Bin 3B).	Workstation B 
	2) Rest the wiring column/silver head into the casing in the orientation shown. 3) Slide the green circuit board into its appropriate slot.	

	4) Slide the charging octagon into its respective slot. Ensure it sits all the way down. 5) Set the switch in its appropriate location.	
	6) Place the yellow slider (Bin 4C) over the on/off switch so that the thumb toggle lies in its appropriate location. 7) Insert a rubber stop (Bin 4A) into a right casing (Bin 4B).	
	8) Snap the two casings shut. Use the charging octagon strip as an alignment aid. 9) Press the silver head into the sealed casings.	
Workstation C		
	1) Insert long black screws (Bin 5A) in the two holes closest to the silver head. Insert two shorter screws (Bin 5B) in the remaining holes 2) Gently screw in all four black screws with the provided screwdriver.	
	3) Slide one black washer (Bin 5C) over each of the two long silver screws (Bin 5D) and each of the two short silver screws (Bin 5E). 4) Use the Phillips head screwdriver to screw in the two long silver screws (with washers) into the top two holes.	



5) Screw in the two shorter silver screws (with washers) into the bottom two holes (underside of the multi tool).

We operationalized the concept of human-AI sensorial contact as nudges and explored how participants perceive the nudges based on their real-time manufacturing performance. In this study, researchers used nudges, carried by sensorial signals to work with participants in the manufacturing workplace. A set of pager devices and a screen were utilized as the carriers to send out nudges to participants. The set of pagers was connected to a control keyboard wirelessly. **Figure** illustrates the pager and the control keyboard used. Each pager was pre-programmed with a number, researchers operated the control keyboard by pressing the number of the pagers on the keyboard to send the nudges.

Figure 5 Nudge Device

During the experiment, the researchers' operation was conducted in a separate room, ensuring that participants were unaware that it was the human operator responsible for sending the nudges. Instead, participants believed that an AI system was monitoring them through video and issuing nudges based on their manufacturing performance. This intentional design by the researchers involves simulating an AI presence to maintain the integrity of the study.

We administered nudges to each participant at pre-determined instances throughout the assembly task. Participants are nudged after they finish assembling a predetermined number of parts. Therefore, this perceived human-AI interaction process has real-time feedback embedded. We administered six individual nudges and one group nudge during the entire experiment. Participants who worked at each workstation were nudged individually after they completed the second and sixth part. After workstation B completed the fourth part, a group-wide nudge was administered. A graphical representation of the nudge schedule for the experiment is shown below in **Figure** .

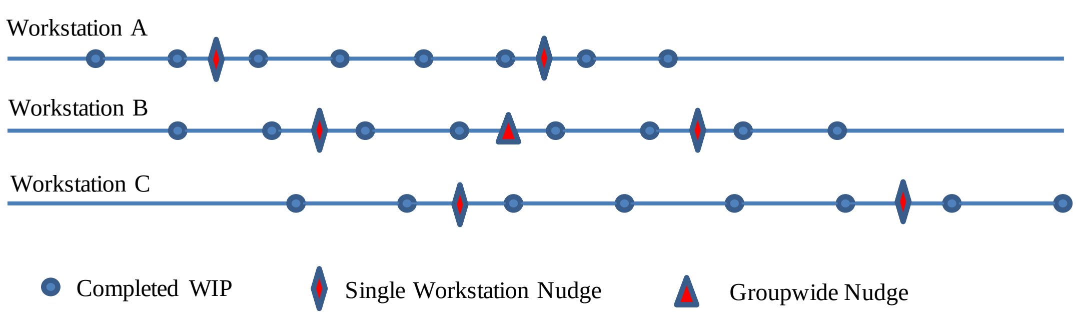


Figure 6 Deployment Timeline of Nudges During Experiment

We also manipulated the salient level of nudges by using three different nudge modalities. The pager devices used in this experiment can beep, light, and vibrate, which represented auditory nudges, visual nudges, and somatic nudges accordingly. Different modalities of nudges indicate different levels of the salience of nudging; that is, auditory nudges are publicly recognizable, for in this study, we placed the pagers on the workstation tables. Whereas participants who received somatic nudges were asked to put the pagers in their pockets, therefore, somatic nudges are detected on a private level. Visual nudges are a combination of both public and private levels, pagers were placed on individual workstation tables, and when researchers sent out visual nudges, only participants who worked at their workstations were able to receive them, which means individual visual nudges were privately delivered. The visual nudges sent to the entire group were presented through the big screen in front of all the workstations, thus publicly presented. The researcher displayed the visual nudges to the group based on the nudge administration timeline. The group-wise visual nudge is indicated in **Figure** .

Figure 7 Group Nudge

We investigated each group exclusively by applying a single nudge modality. Among the nine test groups (G1 through G9), the first three groups received auditory nudges, the next three received visual nudges, and the remaining three groups received somatic nudges. The control group (GC) did not receive any nudges. Recall that each group is comprised of three participants. Detailed group and nudge modalities allocations are illustrated in **Table 4** below.

Table 4 Nudge Modalities Allocations

Group (G_n)	Nudge modality	Sectoral level
G_1 G_2 G_3	Auditory nudge (sound)	Public
G_4 G_5 G_6	Visual nudge (light)	Public

G_7 G_8 G_9	Somatic nudge (buzz)	Private
G_C	None	None

The experiment was video recorded by a camera placed in front of all three workstations with participants' consent. To facilitate the flow of work between the workstations, work-in-progress (WIP) zones, referred to as "buffers," were implemented. Transparent baskets were placed between each workstation, as pictured in Figure 2. Participants stationed at workstation A placed the WIP into the basket after completing the assembly, while participants at workstation B would retrieve the WIP from the basket and proceed with the assembly process. This same process was replicated between workstation B and 3.

The objective for each group was to complete a total of 8 products. To ensure participants were adequately prepared for the assembly tasks, they watched instructional videos on tablets mounted on the workstation table, as well as studied printed paper instructions. Throughout the pre-training phase, the researchers responsible for designing the experiment were present alongside the participants. This pre-training aimed to familiarize participants with the assembly tasks, thereby minimizing any potential impact resulting from their unfamiliarity with the tasks.

The study will start with training (pre-experiment) to expose participants to industry 4.0 principals. The purpose of this training is to determine if formal education on how CPSS functions and the purpose of nudges will improve participants responsiveness to nudges. As noted previously, three types of nudges will be explored. An additional factor studied is whether nudges that sent to a specific individual versus the entire group impact manufacturing performance. Since the types of nudges are naturally different, there is an opportunity to explore if the privacy of the nudges impacts manufacturing performance. Privacy here refers to the ability to hide if a participant is nudged. For instance, a vibrating nudge can be private whereas an acoustic is public. We will also explore how human's perception of their performance affects their responses to nudging. For instance, if the participant considers their performance as well in the task (i.e., they observe their manufacture pace is steady and there are no parts piling up on the WIP before them), will they accept the nudging signals or ignore it. We define the perception representation as private and public, which can be treated objectively. In other words, the investigators decide to send out nudging signals to either a single cell or to all the cells, and it's the participants' choice to perceive the notification either keep it private or tell others publicly. By avoiding the manufacturing performance affected by human action, we stipulate participants in each cell are not allowed to walk to help others, but they can talk to each other in the process. A breakdown of the experiment factors and levels is shown below in **Table 5**.

Table 5 Experiment Factors and Levels

Factors	**Levels**		
Nudge Type	Visual	Auditory	Somatic
Recipient	Individual	Group	
Privacy	Public	Private	
WIP	None	Low	High

Participants will take part in the manufacturing process in which the technological devices will constantly offer information that pertains to their decision-making during the process. Through exposure, the participants will have an experience of nudges by visual, auditory, and somatic inputs [85]. Auditory nudge signals and visual nudge signals can be perceived either individually or within groupwide, but somatic nudge signals can only be detected individually. Researchers will observe the participants' behavior and record the time distributed to each process in the assembly line throughout the experiment by using recording tools. Thus, qualitative data and quantitative data will be collected for research analysis. After the experiment, interviews were conducted to explore the participants' reactions and responses to nudge signals. Researchers will assess the emotional tone of the participants' language in relation to the topics present in their raw interview script. Quantitative data such as throughputs, manufacturing errors, and time used on each cell before and after nudging, etc., will be recorded. By reading the data collected in a computationally statistical way, this pilot study will convert the language data into statistically processable data; by doing so, this study can see whether there is any difference among groups in perceiving the sudden changes triggered by technological devices, and predictions on time spent at each cell can be made by using computational model, hence proposing guidelines on improving manufacturing efficiency. The sequence of interaction between human and AI devices is shown in the **Figure** below.

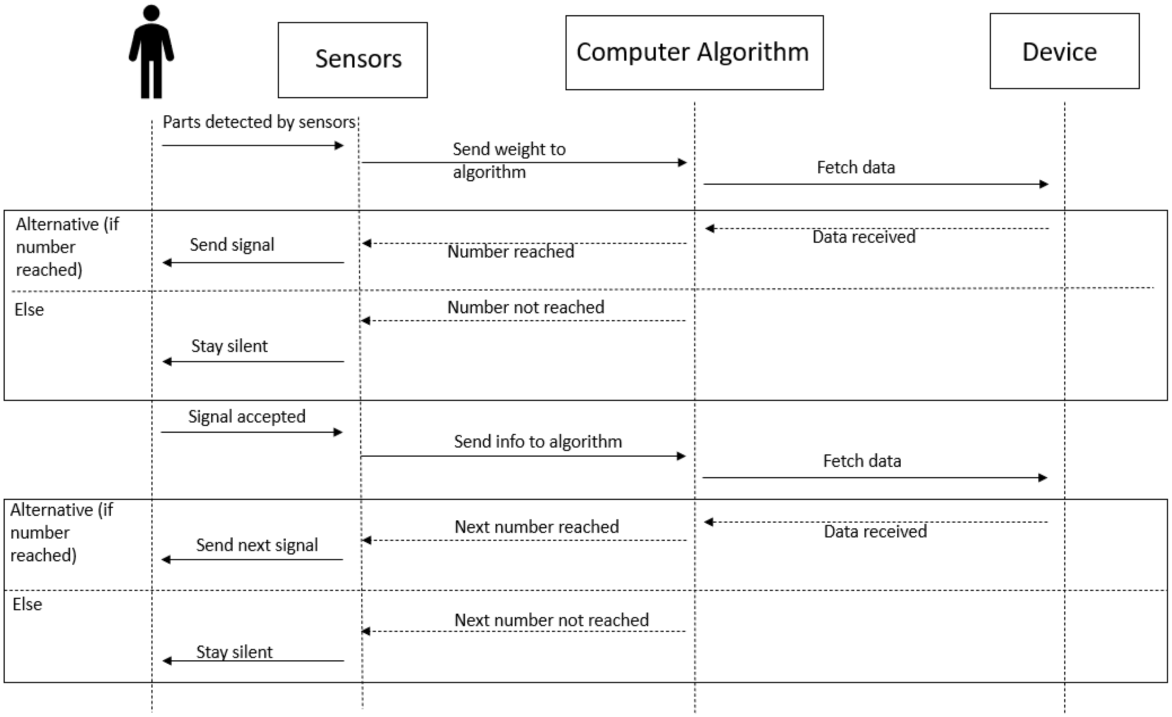


Figure 8 Experiment Sequence Diagram

3.3 Experiment Flow

Nudging equipment that will be used in the experiment is a set of pagers. Pagers can be remotely controlled by a keypad transmitter. Multiple prompts modes include vibration (somatic), flashing (visual), and buzzing (auditory). In designing the workflow in the laboratory setting, this study will consider displaying nudging signals through the pager randomly to each cell in the assembly line. In the future, using moving robots as nudging device is the next step. Participants will be randomly assigned to each scenario where different treatments and formats of nudge signals are combined. Sending nudging signals would likely cause the behavioral, affective, and cognitive changes of individuals as their choices are affected by the technological devices.

Pre-experiment: Participants will be administered a survey to collect demographic information and information related to their experience performing manufacturing (for example, questions to determine if they have worked in a manufacturing setting before). After completion of the survey, each group will be given formal training (i.e., lecture-based; unilateral communication), informal training (i.e., inquiry-based, bilateral communication), or no educational interventions before their experience in a manufacturing line that includes nudging.

Experiment: After training, participants will be asked to take part in the manufacturing process. The handheld tool will be properly dismantled and each participant on the line will be assigned to an assembly cell. During the manufacturing process, participants will periodically be exposed to a form of nudging (visual, auditory, and haptic) based on the experimental group they are in. Within all the test groups, one group will be selected randomly with a hidden camera for measuring the Hawthorne effect. Throughout the manufacturing assembly process (which we anticipate to last 20 minutes), we will videotape participants for post-experiment measurements and tally all the parts assembled.

Post-experiment: The post-experiment interview will be conducted to get qualitative data. The interview will be developed based on a formal interview protocol. The interview will be administered to participants after the experiment is completed. Interviews will be completed individually with each participant. Interviews will last approximately 30 minutes. The flowchart of the proposed experiment is shown in **Figure**

.

In the proposed experiment, all the research questions are addressed within the “test” portion of the experiment flowchart, where nudging is administered. Research Question 1 is addressed by determining the impact of nudging on human response as measured by manufacturing performance (takt time, number of errors, etc.). We observe how the human respond when a nudge is administered by comparing various manufacturing performance metrics pre and post nudge. Research Question 2 is addressed by considering varying types of nudges to determine if there are changes in relative manufacturing performance when nudge types change. Research Question 3 is addressed by presenting the human with conflicting cues than that of the nudge and observing human response.

Figure 9 Experiment Flowchart

3.4 Data Collection and Analysis Methodology

The proposed study will evaluate the model on datasets based on the extracted data from the experiment. The raw data will be collected into two formats, one is numerical numbers (quantitative data) and the other one is context (qualitative data). **Table 6** shows the detailed quantitative data and qualitative data, definitions are explained in the context of manufacturing assembly line.

Table 6 Data Types

Name	Definition	Formula
Throughput	The number of parts produced over a specified time period	$\frac{\text{number of units produced}}{\text{time}}$
Cycle time	The time takes to complete one product	$\frac{\text{production time}}{\text{number of units produced}}$
Error rate	The frequency of failures in assembly line production	$\frac{\text{number of parts failed}}{\text{number of parts produced}}$

Name	Definition
Video data	Video file format to record behavioral changes
Interview data	Surveys and questionnaires

In this study, we designed a nudge-guided experiment to observe and measure participants' manufacturing performance by coding their assembly cycle time values used for assembling each part from the video recordings. Cycle time defines the time required to complete one cycle of a process, in this experiment, each participant's cycle time is the time takes to finish one unit of the assigned task (measured in seconds). For this study, we only use workstation cycle time as the key indicator for participant's manufacturing performance, and is the only dependent variable discussed throughout the whole paper. Shorter cycle time values represent better manufacturing performance., Each participant has 8 cycle time counts since the assembly task for each group is to assemble 8 power tools.

We performed three statistical analyses to address the research questions. For the first research question, by grouping the data into three sets according to three nudges along the timeline that each participant will receive, each set has two groups of data referring to the assembly cycle time before and after nudges, t-tests were used to determine whether there is a significant difference between the assembly cycle time mean before and after nudged. In this study, statistical significance is considered at $\alpha<0.05$. The scatter plot helps to visually display the cycle time comparison between groups who received the nudges and the group who didn't receive the nudges. We also applied a line chart to graphically understand the significance of nudges, patterns of how nudges function throughout the assembly task can be found by plotting the line chart and it is useful for forecasting how nudges will function if the assembly line task expands timewise.

For the second research question- which explores the impact of different modalities of nudges on participants' manufacturing performance – ANOVA analysis was used. We grouped the data by different modalities of nudges that participants received. The statistical significance is selected at $\alpha<0.05$. ANOVA was applied to test the existence of the significance of nudges. Followed by the post-hoc analysis, which was used to determine which groups were significantly different from each other. The advantage of combining ANOVA and post-hoc analysis it allows one to identify which group has significant differences from one another, thereby, obtaining precise and comprehensive insights into disparity among the groups. Lastly, boxplots provided an aid to visualize the distribution of data.

Third research question on what are the other factors that contribute to the human manufacturing performances, was explored by coding the video data. Quantitative data (i.e., cycle time) was extracted from the video and visualization method was displayed. We compared the cycle time that the participant used before and after getting technological nudges, and most importantly, before and after getting social cues, which are considered as social environment nudges. The bar visualization technique was deployed to display the quantitative data coded from qualitative data.

CHAPTER 4

RESEARCH FINDINGS AND DISCUSSION

This chapter discusses three different vignettes. We break the research findings into three distinct perspectives: findings on technology, findings on humans, and findings on social factors. By the end of the chapter, these perspectives are interconnected.

4.1 Impact of AI-Guided Nudges

Each assembly line task was completed by a group, consisting of three participants, who were randomly assigned to one of the three workstations. Each participant was required to finish 8 parts regarding the assembly line task. **Figure 10 Δ** Distribution Among Test Groups and Control Group shows all the cycle time range (**Δ**) distributions of test groups and control group. **Δ** is the cycle time difference between two sequential assembly parts, which can be calculated through the formula below, **Δ**$= t_i+1-t_i= t_i+2-t_i+1= \ldots$ $(i>=0)$, where t stands for cycle time and i notates the imaginary quantity of the parts. Square shape data points represent the mean values of **Δ** for all the test groups and round shape data points denote the **Δ** values for the control group.

In this figure, data points that are located below the bold line are negative, meaning the cycle time used between the sequential parts decreased, thus indicating the human operators worked faster and the manufacturing performances improved, and vice versa. Eight parts were assembled by each participant, as a result, each participant should have seven data points referring to the number of part intervals. X-axis represents the intervals between the parts, for example, the first data point indicates the time difference between the first assembly part and the second assembly part. The y-axis shows the range of the time intervals, the values of **Δ** fall between -0.2min to 0.2min. The valuable zone (green) and the valueless zone (red) are divided with respect to zero (bold line). Dash lines represent the point when nudges were sent out to the participants. It was observed that in the test groups, more than half data points (square shape data points on x-axis, scale mark 2, 4, 6, and 7) are less than zero, which is to say, the time that the human operator used on 3rd part, 5th part, 7th part, and 8th part declined, thus nudges have accelerated the cycle time that human operators used for four times out of seven. However, in the control group, only three data points out of seven are below zero, which means that human workers who received nudges had a higher percentage of manufacturing performance improvement. As a result, nudges hold promises of leveraging human operators' manufacturing performances.

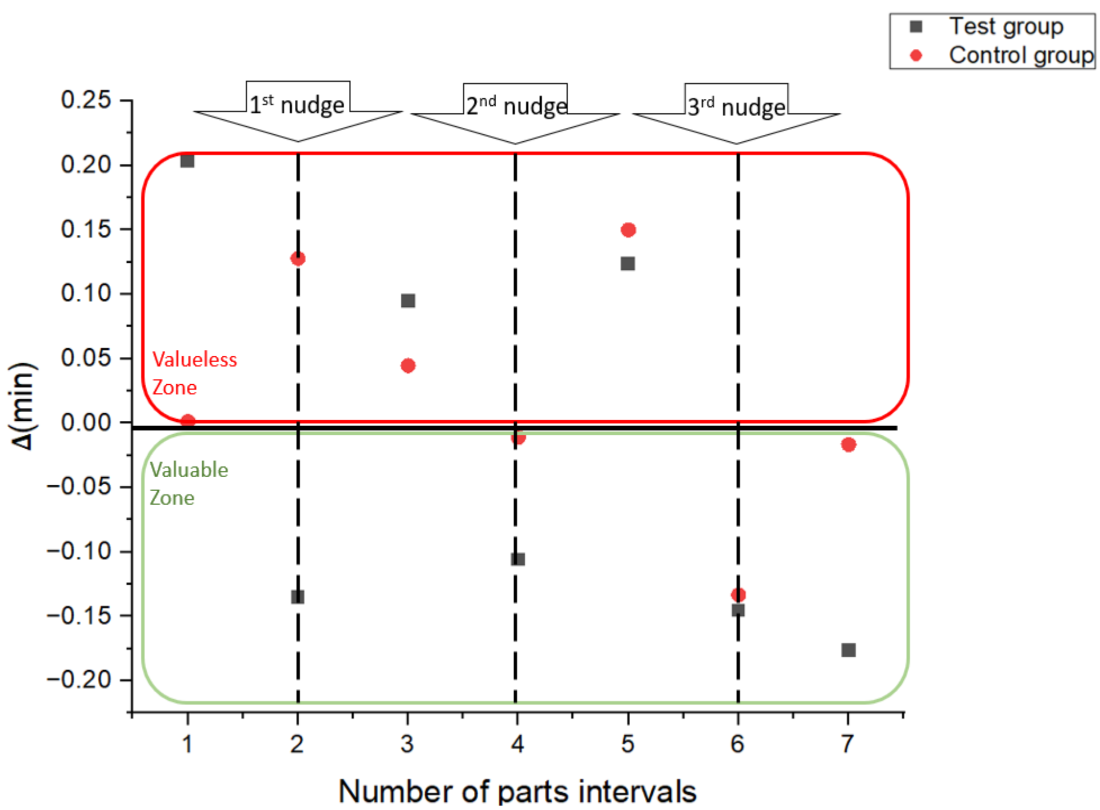


Figure 10 Δ Distribution Among Test Groups and Control Group

To address the fundamental research question, three t-tests were conducted separately for three nudges. The first t-test was performed between the cycle time spent on assembling the second part and the third part for all participants in test groups, where each participant received their first nudge after they finished assembling the second part. **Table 7** T-test Result for the Existence of Impact: First Nudgeshows the results of the first nudge's impact. It was observed that p=0.038 (<.05), which means the first nudge is identified to have significance on human operator's manufacturing performance. It is also noticed in the table that the mean value for assembling the part dropped from over 2 minutes to less than 2 minutes, additionally proving the existence of the significance for the first nudge.

Table 7 T-test Result for the Existence of Impact: First Nudge

Cycle time (min)	Time used on 2^{nd} part	Time used on 3^{rd} part
Mean	2.094	1.969
Variance	0.782	0.906
Pearson correlation	0.932	-
t Stat	1.846	-
p-Value	0.038	-
t Critical	1.708	-

Table 8 T-Test for The Existence of Impact: Middle Phase Nudgeis the t-test result for validating if the second nudge can result in human operators' manufacturing performance changes. The second nudge was sent out to the person who was at workstation 2 among all the test groups. After they have done the 4th part. The p-value generated from the second t-test for the second nudge (0.045) is still less than the predefined α (0.05), indicating the second nudge (middle phase nudge) still contributes to the improvement of the manufacturing performances. Notably, the p-value for the second

nudge (0.045) is bigger than which of the first nudge (0.038), illustrating the power of the second nudge is weaker than the first one. Similar to the first nudge, the mean value of the cycle time used between the 4th part and the 5th part decreased, corroborating the finding on the existence of significance for the second nudge.

Table 8 T-Test for The Existence of Impact: Middle Phase Nudge

Cycle time (min)	Time used on 4^{th} part	Time used on 5^{th} part
Mean	1.946	1.827
Variance	0.654	0.530
Pearson correlation	0.913	
t Stat	1.769	-
p-Value	0.045	-
t Critical	1.714	-

Participants obtained their last nudges after they assembled the 6th part. As shown in **Table 9** T-test Result for the Existence of Impact: Last Nudge, The P-value in the third t-test (0.468) is far beyond 0.05, which implies the third nudge does not have any impact on performances. Despite the drop in the mean value for assembling the 6th part to the 7th part, the significance result disclosed the non-existence of the third nudge.

Table 9 T-test Result for the Existence of Impact: Last Nudge

Cycle time (min)	Time used on 6^{th} part	Time used on 7^{th} part
Mean	1.977	1.966
Variance	0.532	0.448
Pearson correlation	0.553	
t Stat	0.08	-
p-Value	0.468	-
t Critical	1.721	-

The mean value of cycle time used per part is exhibited in Figure 12, the x-axis indicates the number of parts that the participants finished while the y-axis is the cycle time spent on assembling each part. It has raised attention to the oscillation of participants' manufacturing performances. Taking the participant who worked at workstation 2 as an example, nudges were sent out at three specific time points, at the time when the participant completed the 2nd part, 4th part, and 6th part. Cycle time dropped rapidly after the person got nudged, accompanied by gradual resilience back to the original state throughout the entire experimental task. The cause of the overall steady state with regular fluctuation is ascribed to the time-related property of nudges, precisely speaking, the property of instantaneousness. The pattern shows in **Figure 11** Cycle Time Mean Fluctuation echoes the vibration in **Figure 10 Δ** Distribution Among Test Groups and Control Group.

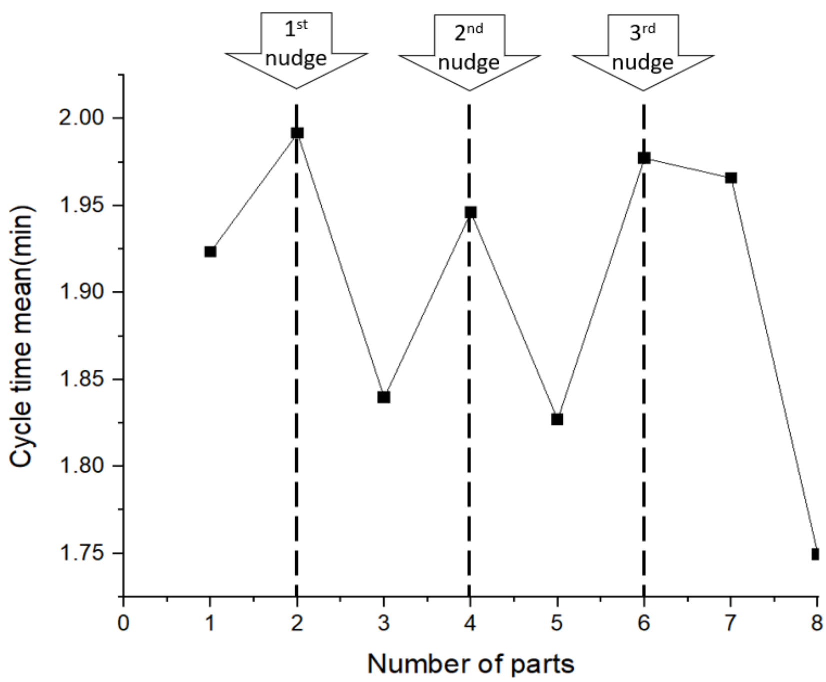
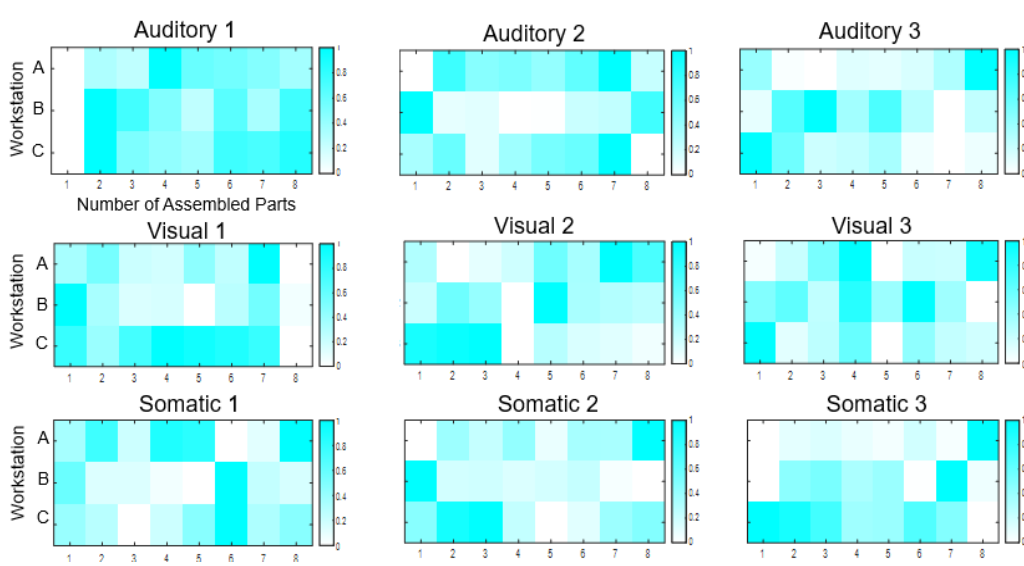


Figure 11 Cycle Time Mean Fluctuation

The data distribution plot shows that in manufacturing assembly lines, the presence of nudges affects human operators' manufacturing performances, explicitly, in a positive direction. Nonetheless, further results in the t-tests for three different nudges show that the impact of nudges is not consistent. From the first nudge, second nudge to the last nudge, the p-value increased from 0.038 (has significance), 0.045 (has significance) to 0.468 (no significance), indicating the significance of nudges doesn't exist throughout the entire assembly task, instead, the significance recedes as the task progressed and disappears in the end. The line chart reflects the vibration of cycle time used per part, the cycle timeline swings in a regular pattern, and cycle time only dropped after the human operator got nudged, and goes back up again. It's interesting to observe the pattern of how nudges work and the instant capability of nudges, such outcomes prompted the thoughts on the potential factors that caused these results, one of the factors is individual fatigue, as deducted in the results shown below in

Figure *1*.



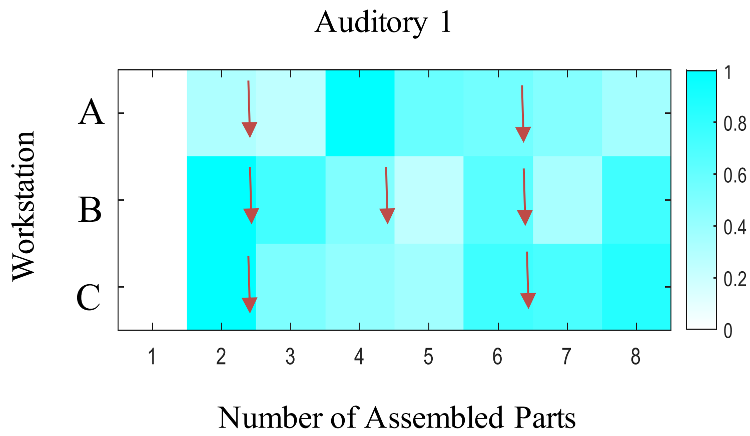
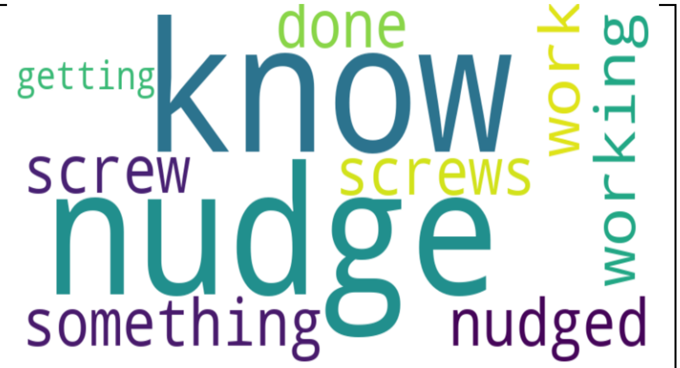


Figure 1 Cycle Time Heatmap

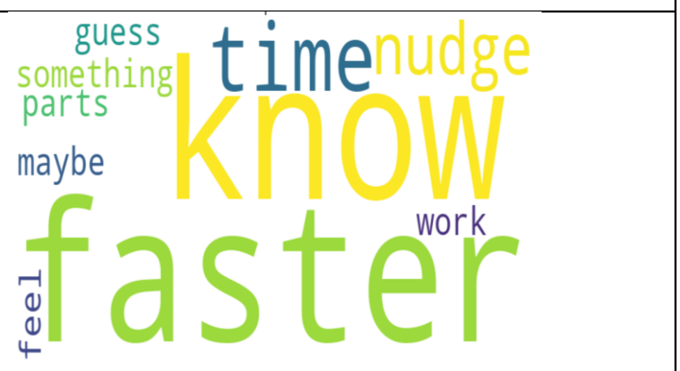
Heatmaps are generated regarding the manufacturing cycle time of each participant at their own workstations. Each cell in the heatmap corresponds to a specific workstation assembling a certain number of parts. The color intensity in each cell of the heatmap represents the normalized value of the cycle time data. The darker the color is the higher the value it represents, meaning the human operator requires longer assembling time, and vice versa. The data is normalized row-wise. The arrows are the time point where we send out the nudge signals. As it shows, after delivering the nudge signals, the color of the sequential cell turns dim, for both individual nudges and group-wide nudges, which proves that nudging did have a significant impact on cycle time. That was beyond that of the normal deviations that get on the line per part.

Interview scripts were gathered at the post-experiment session and asked the participant what's their thought, and how they felt about nudges. Worldcloud, which is a visualization technique to represent the text data, as shown in **Table 10** Wordcloud below, words "know" "nudge" "faster" "time" have higher frequency and importance compared to other words, people are aware of they are being nudged and they need to work faster.

Auditory



Visual



Somatic

Table 10 Wordcloud

This also echoes to the previous quantitative analysis; nudge does have a positive impact on reducing human operators' manufacturing assembling cycle time. Another factor can be the format of nudges, which is discussed in the following session.

4.2 Impact of Nudge Modalities

The second research question seeks to diagnose if different modalities of nudge can affect human operators' manufacturing performances. The first research question has addressed the existence of the significance of nudges and how nudges function throughout the assembly tasks, following analyses are conducted based on the establishment of the first research question.

Table 11 presents the ANOVA analysis of the significance of nudges among different modalities (the modalities are displayed in the format of "sensorial-sectoral", which are auditory-public, visual-combination of being public and private, and somatic-private). In this analysis, the statistical significance level α is still considered to be 0.05. We counted the mean value of each participant's cycle time (only for the test groups, built on the first research question), data were divided into three sets and grouped by the modalities of nudges that participants received. The P-value between the three groups (<0.001) is substantially smaller than the preset α (0.05), revealing that different modalities of nudges affect human operators' manufacturing performances. It is also observed that the groups who received somatic nudges (private nudges) have the smallest cycle time mean value, which represents the best manufacturing performances, followed by the groups who were treated with auditory nudges (public nudges). While the visual nudges (combined nudges) groups hold the largest cycle time mean, speak for the least favorable manufacturing performances.

Table 11 ANOVA Result for The Cycle Time Means Among Three Modalities for Test Groups

Groups	Count	Sum	Average
S	72	144.688	2.01
Visual	72	194.717	2.704
Somatic	72	129.61	1.8

Source of Variation	SS	df	MS	F	*P*-value
Between Groups	32.264	2	16.132	12.191	0.00000971
Within Groups	281.87	213	1.323		
Total	314.134	215	1.800		

The following investigation naturally falls into the examination of significant differences between the three groups. The average cycle time values that are categorized into three groups regarding different nudge modalities are used to conduct the analyses. In **Table 12**, the result of the Bonferroni test is 0.017, independent t-tests were conducted to look for the difference between pairwise groups (auditory and visual, visual and somatic, auditory and somatic, sectoral-level speaking, public, private, public and private). P-value (0.002) generated from the auditory and visual groups (public and combined) and which (<0.001) generated from the visual and somatic groups (combined and private) are both less than 0.017, implies the impact of nudges in these two groups are more significant than the impact of nudges in the auditory and somatic (public and private) groups. Here, note that significance only indicates visual (public) nudges cause the performance differences between human operators' groups that got the auditory (public) nudges and the groups who received visual (public) nudges, as well as the visual (public) groups and the groups that received somatic (private) nudges, the existence of significance doesn't imply any positive or negative effect.

Table 12 Bonferroni Correction Between Groups with Different Modalities of Nudges

Alpha	0.05
Post-hoc test (Bonferroni corrected)	0.017

Group	*p*-value (t-test)	Significant?
Auditory-Visual	0.002	Yes
Auditory-Somatic	0.091	No
Visual-Somatic	0.00003	Yes

Results from the first research question have proved that the last nudge does not have any impact, hence, only exploring the first two nudges transmitted through different modalities can further solidify the impact that different modalities of nudges can bring to the manufacturing performances changes.

In **Table 13**, on the left side, **Δ** is calculated using equation (1), where i= 2. **Δ** values in the first column show the cycle time differences that are initiated by the first nudge for participants who received the auditory (public) nudges, same in the second and the third column, represent the cycle time differences in visual (combined) groups and somatic (private) groups. Negative values indicate that the cycle time decreased after the participants got nudged, thus the manufacturing performances augmented. After we added up **Δ**s in the same group, the sum of the somatic (private) groups is the lowest, which implies the impact of somatic (private) nudges is the strongest among the three modalities. The values on the right-hand side are the cycle time distinctions sparked by the second nudge for three modalities. It is also noticed that the sum in the somatic (private) group remains to be the smallest for the second nudge.

Δ (min)	**Auditory**	**Visual**	**Somatic**
	0.483	0.25	-0.95

Δ (min)	**Auditory**	**Visual**	**Somatic**
	-0.617	-0.217	

	0.817	-0.9	-0.033
	-1.85	-0.367	-0.083
	0.217	0.2	-1.2
	-0.617	0.167	0.383
	…	…	…
	0.783	1.2	0.3
Sum of **Δ**	>0	>0	<0

	-0.4	0.35	-0.117
	0.45	-0.003	-0.317
	0.017	0.4	-0.117
	0.133	0.5	-0.2
	…	…	…
	0.15	-0.067	0.05
Sum of **Δ**	>0	>0	<0

Table 13 List of **Δ** Triggered by the First Nudge (Left) and by the Second Nudge (Right)

In response to the significance of somatic nudges, **Figure** and **Figure** help visualize the performances comparison better. As illustrated in Figure 8, the cycle time mean of participants in the somatic (private nudges) group is smaller than the cycle time mean in the auditory (public nudges) and visual (combined nudges) groups, as well as in Figure 9. Those comparisons reveal that from the perspective of nudge modalities, somatic nudges outperform auditory and visual nudges, from the sector level, private nudges function the best.

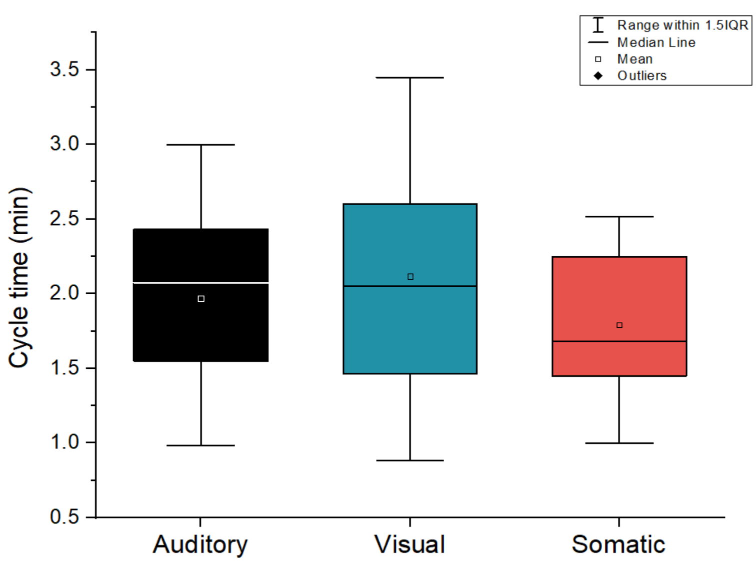


Figure 13 Manufacturing Performances Comparison between Different Modalities of Groups-First Nudge

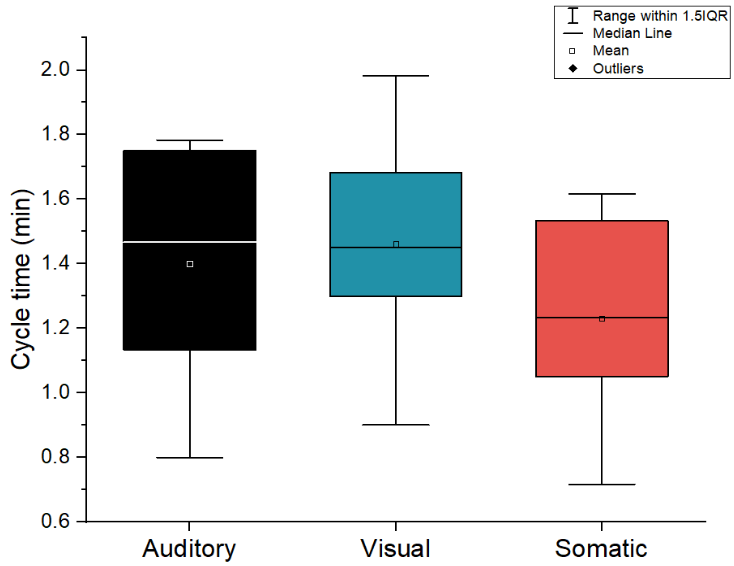
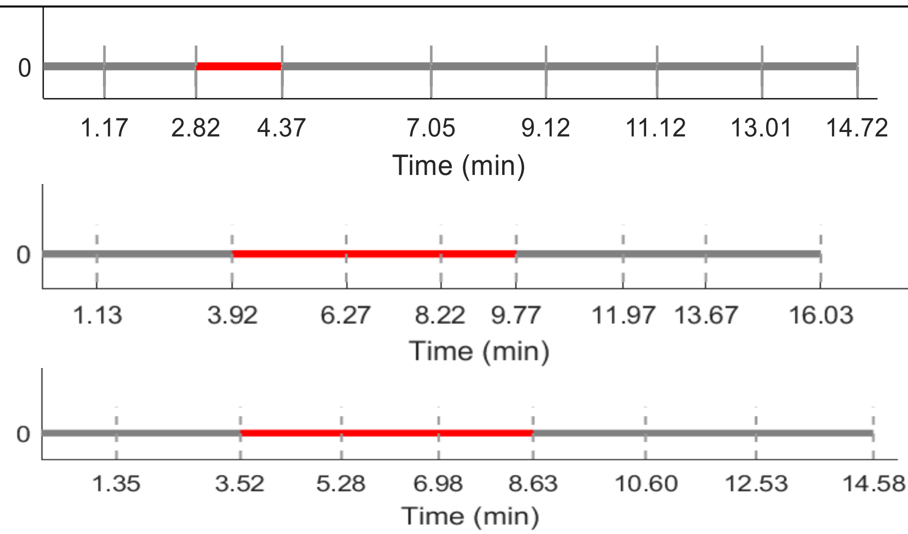


Figure 14 Manufacturing Performances Comparison between Different Modalities of Groups-Second Nudge

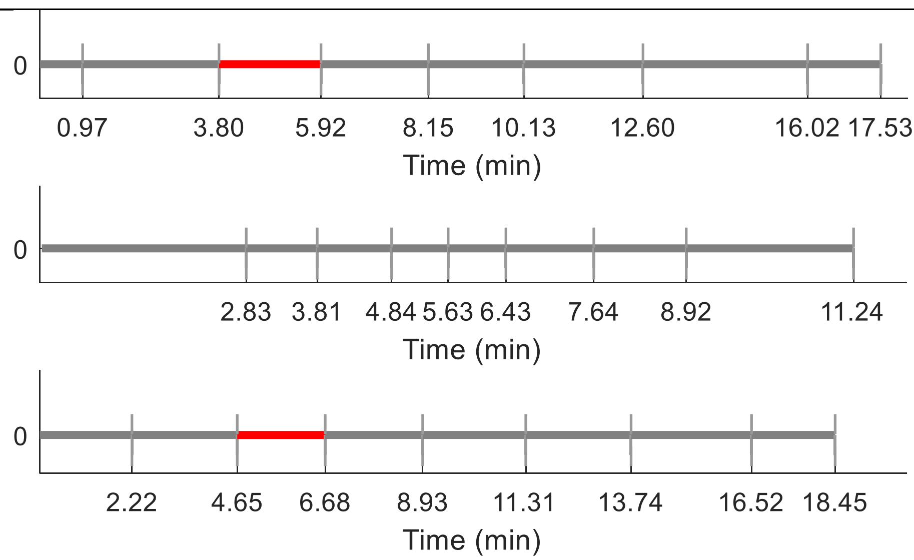
The impacts of different modalities of nudges on human operators' manufacturing performances vary. The result from the ANOVA test (<0.001) is significantly smaller than 0.05, confirms the modality of nudges is a factor that causes human operators' manufacturing performances differences among groups. Post-hoc test then addressed the existence of significance among three modalities. Since the last nudge in the assembly line task doesn't have any impact, we grouped the samples by the modalities of nudges they received for the first nudge and the second one, the outcomes show the sum of cycle time differences triggered by the somatic nudges for the first nudge and the second nudge are both the smallest out of three modalities, equivalently, the significance of private nudges ranks the highest. Mean value allocation in the boxplots then supports this finding.

4.3 Manufacturing Workplace Human Factors

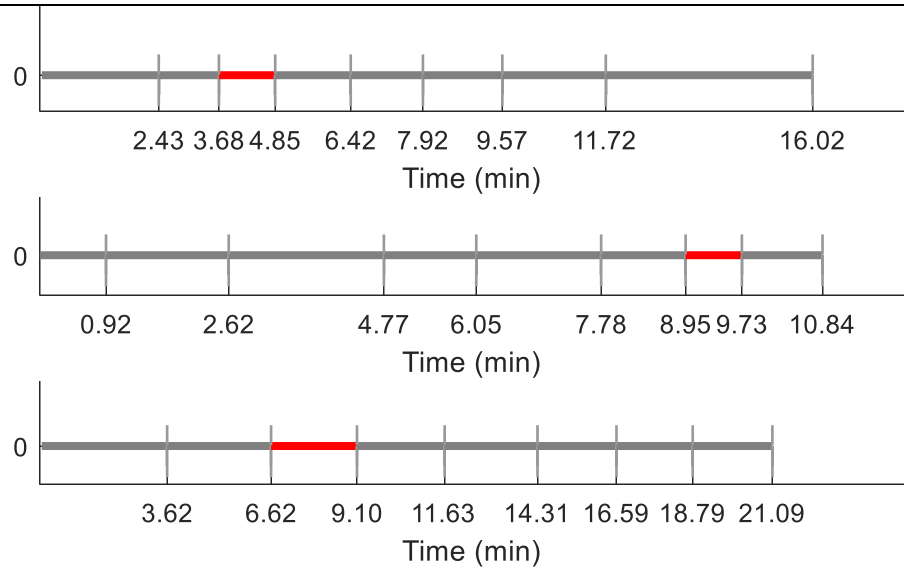
Other factors that could impact a person's reception to a nudge exist. From operational research, studies suggest that social cues could impact a person's reception to a nudge. In the field of psychology, there's shame could impact a person's reception. . In manufacturing assembly line, environment, social cues have a huge impact on human operators' perception, behavior and hence working performance. Emphasizing social cues design can guide human operators towards the organizational desired goals. Factors such as workplace layout, social norms direct human behaviors from cognitive perspective. The current manufacturing environment has evolved to a smart workplace that requires more communication between human operators and smart technology compared to traditional manufacturing environments. From an exploratory perspective, we measured the human operators' cycle time and did a comparison investigation between the cycle time reduction and whether human operators got nudged through the nudge devices or got nudged through their social environment, which refers to social cues. The bar visualization for each group is listed as follows in **Table 14** Cycle Time Bar Visualization. The range of the nudge, which is how long the nudge lasts, is plotted. Since each participant is required to finish 8 assembly parts, each person has 8 manufacturing cycle ranges. The red part in the bar represents the high alert range that the nudge signal can last, which means how long the nudge stimulation can function on human operators' manufacturing performances. It is observed that the later in the assembly task, the shorter the nudge that lasts. It is suggested that this could be due to information overload and human fatigue. If the nudge frequency is too high, human operators are going to start to get diminishing returns.



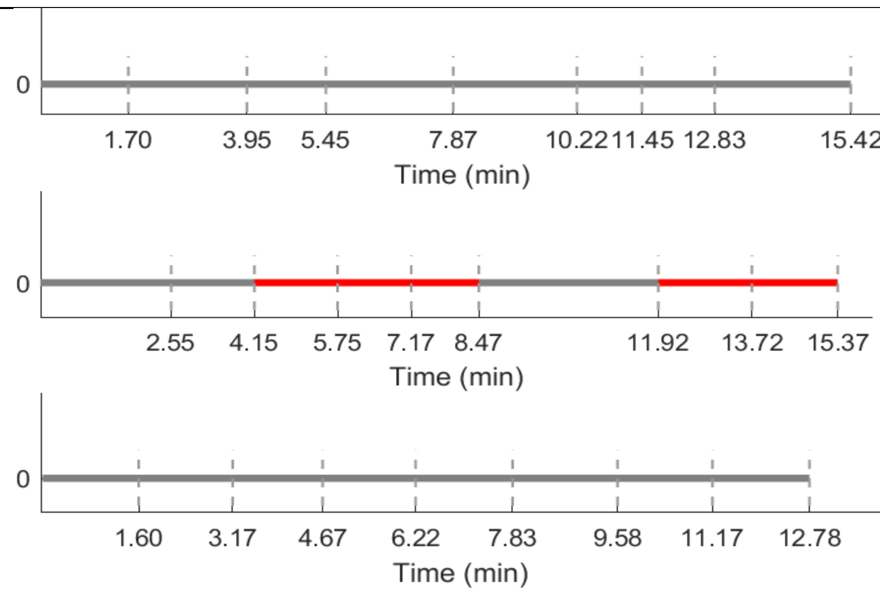
Auditory Group 1: Workstation A, B and C (from the top)



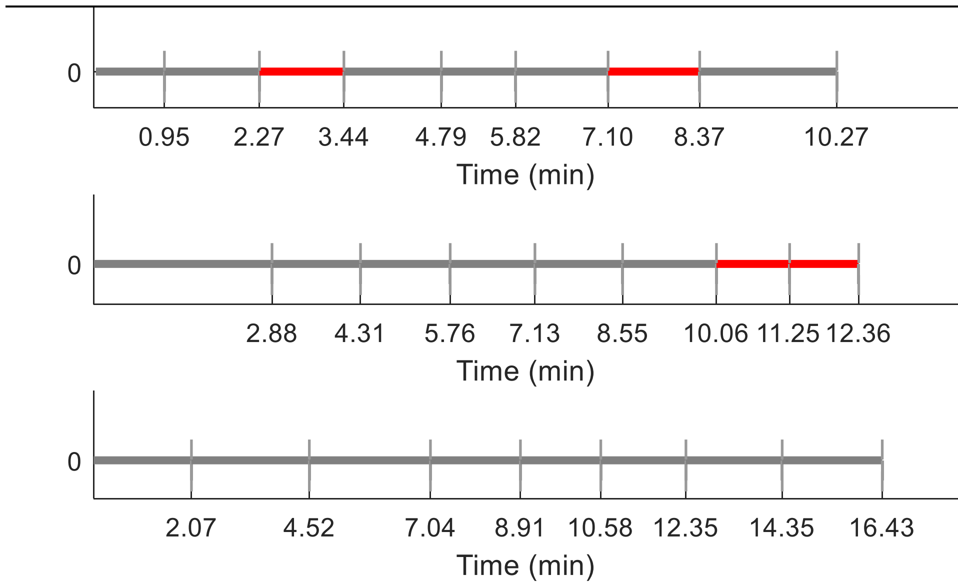
Auditory Group 2: Workstation A, B and C (from the top)



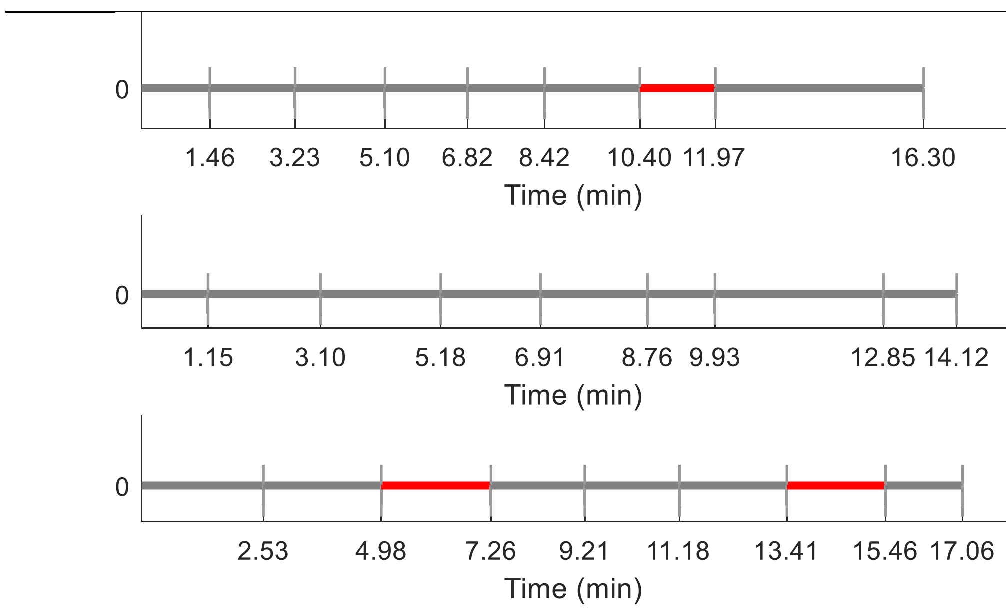
Auditory Group 3: Workstation A, B and C (from the top)



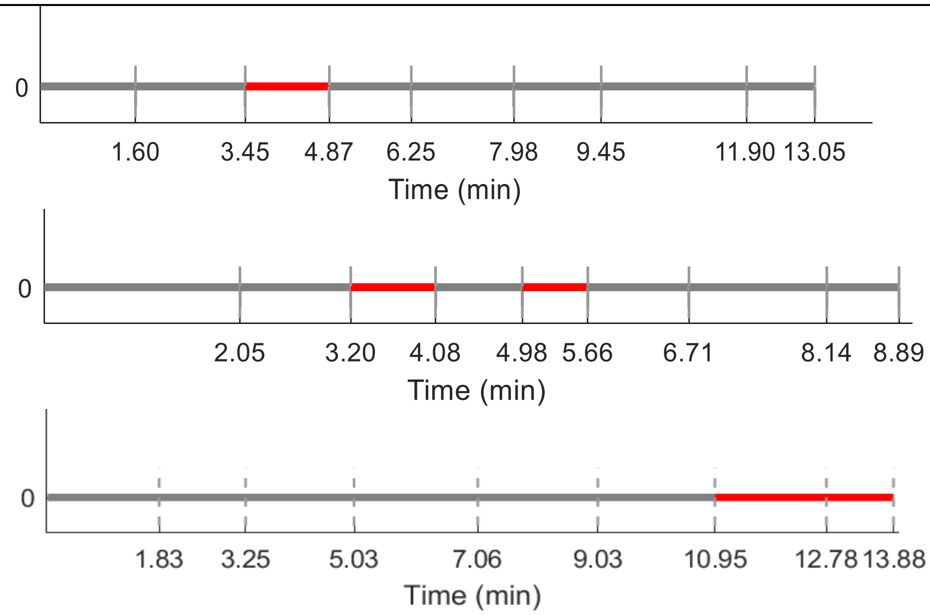
Somatic Group 1: Workstation A, B and C (from the top)



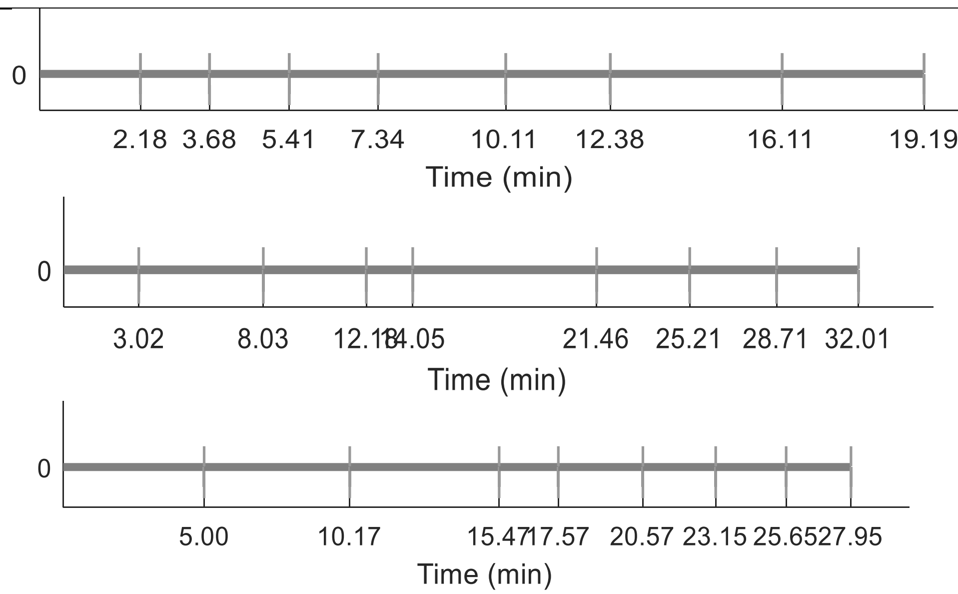
Somatic Group 2: Workstation A, B and C (from the top)



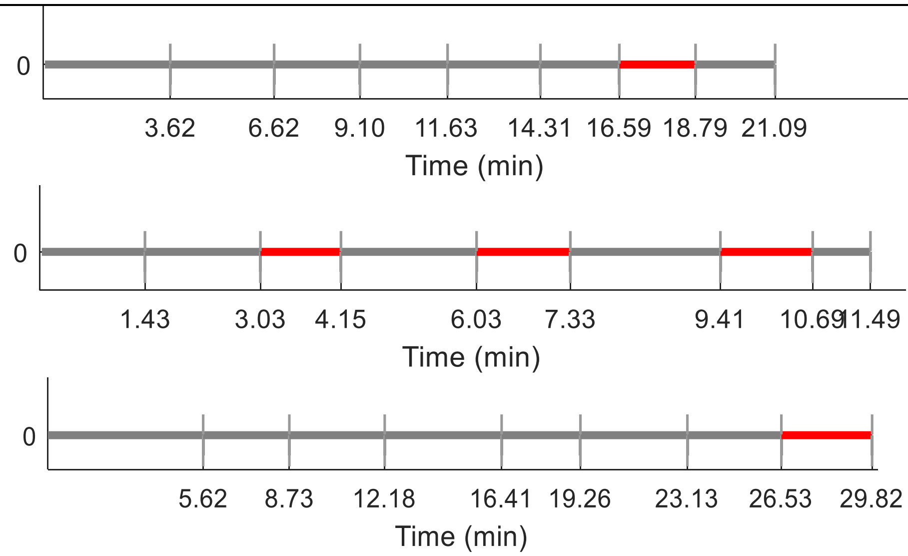
Somatic Group 3: Workstation A, B and C (from the top)



Visual Group 1: Workstation A, B and C (from the top)



Visual Group 2: Workstation A, B and C (from the top)



Visual Group 3: Workstation A, B and C (from the top)

Table 14 Cycle Time Bar Visualization

As this is a protocol study and the phenomenon that emerged in the following hasn't been investigated yet. It is observed that the participant who works at workstation B in the third somatic group as an example, we picked out the time when no WIP is piling in both buffer zones when they only get the nudged, the cycle time used is longer than they used when they saw there are WIP piled up and there is no nudge. It is found out that human operator put greater priority on their social and environmental cues than they did on the nudge from the AI devices. In other groups' data in fact, nudges were ignored as if it was really a non-factor. This cyber-physical-social phenomenon shows the level of agency the humans believe they have in this complex system. And this finding shows that humans will value their environmental and social cues more so than how they value AI, shown in **Figure** below.

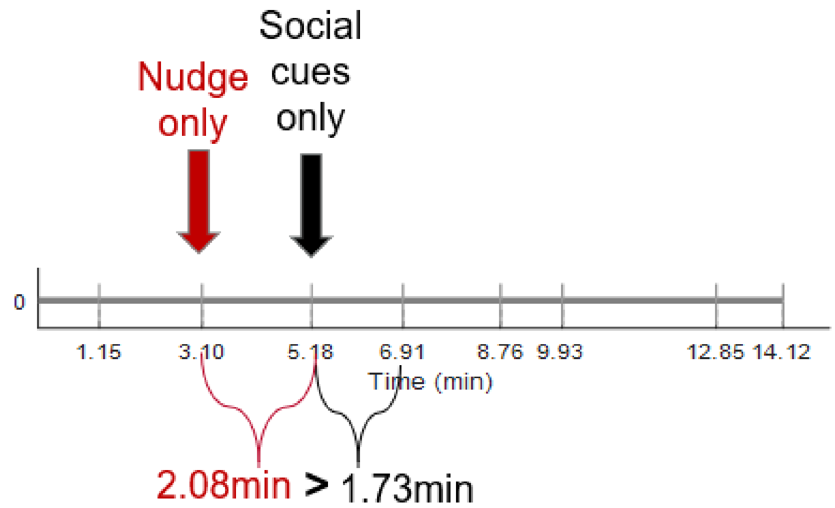


Figure 15 Cycle Time Comparison

4.4 Research Discussion

The evolvement of CPS with human in the loop represented a significant leap toward smarter, more efficient manufacturing processes. The intertwined relationship between human operators and AI requires a deeper understanding of the interaction between them, for the interaction between these two elements adds complexity to modern manufacturing settings. This must be understood to guarantee the manufacturing assembly lines can be optimized in the correct direction. AI technologies are designed to assist with manufacturing human operators' decision-making processes and thus guide them to better manufacturing performances. Current CPS includes sensors and computer algorithms that are capable of performing complex tasks such as big data collection and real-time data analysis. Manufacturing plants are an assembly that includes CPS and human operators working simultaneously. CPS provides human operators with feedback after data analysis to achieve the goal of a closed loop. However, overall manufacturing performance heavily depends on the design of CPS, the manufacturing assembly environment, and human operator perception.

We introduced the nudge theory to manufacturing research. Nudge theory was originally from behavioral economics, the concept indicates the redesign of human choice architecture towards desired outcomes without restricting the freedom of choice. In the manufacturing assembly line settings, the utilization of nudge has a huge potential by reshaping the manufacturing plants by guiding human operator behavior, ensuring adherence to protocols, boosting productivity, and increasing job satisfaction by considering workers' well-being. By redesigning choice architectures that aligned with human cognitive biases, nudges led to significant improvements in manufacturing performance and efficiency.

Applications exist in the current manufacturing settings such as sound alerts, which reminded operators to take safety precautions or notify them of potential issues that need immediate attention. Visual nudges such as indicator lights, remind human operators through highlighted areas where errors have occurred. Some somatic nudges, such as vibrations, alerted operators to deviations from standard operating procedures or signaled the completion of specific tasks. The involvement of these nudges within modern manufacturing settings indicates there's a demand for a deeper understanding of human behavior, and cognitive load, for the redesign of the manufacturing environment. Factors within the design of nudge such as frequency, timing and modalities should be considered to ensure the effectiveness of nudge and human operator workflow without causing undue stress or distraction.

This study employed a mix-method approach. To investigate the impact of nudges on human operators' manufacturing performance, we combined quantitative analysis from performance metrics with qualitative insights from operator feedback. By analyzing the data, we identified the patterns and correlations were identified that revealed the effectiveness of different designs of nudges in improving performance. This approach also helped understand the subjective experiences of workers, providing a holistic view of the human-AI interaction. The experiment framework is shown below in **Figure** .

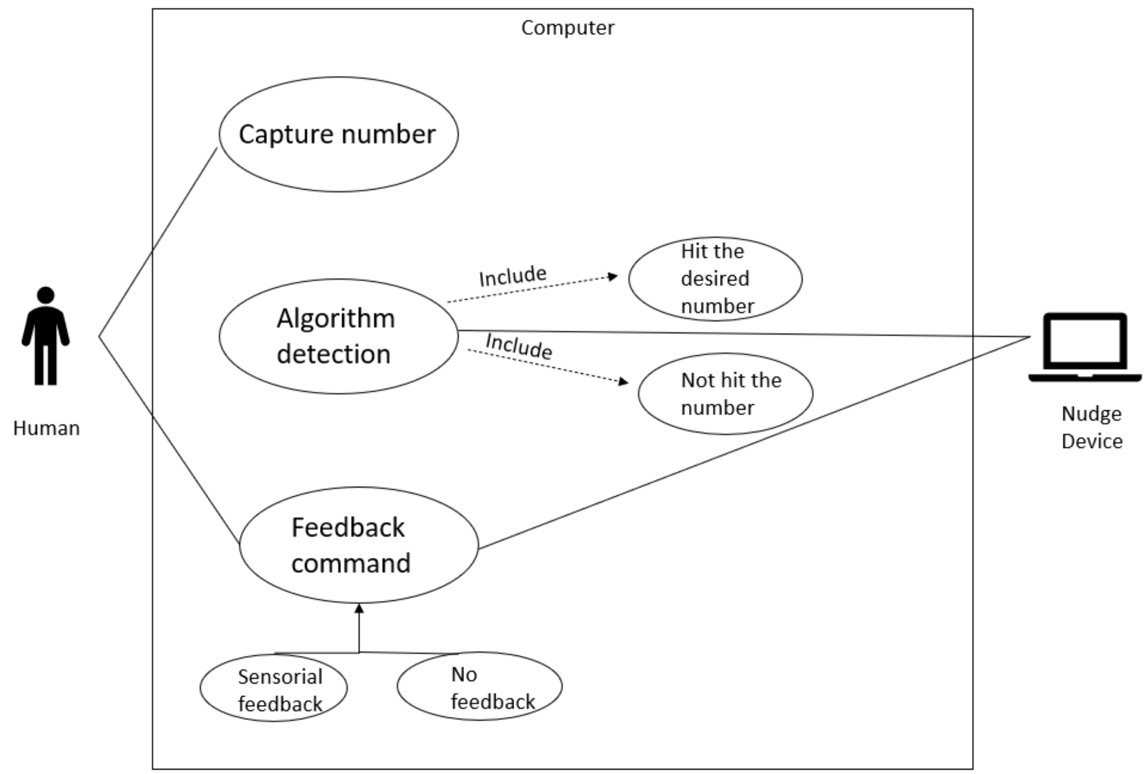


Figure 16 Experiment Framework

In this study, we conducted a manufacturing assembly line experiment to examine the mechanisms of the impact of nudges on human operators' manufacturing performances. The first research question first examines the existence of the impact of nudges on human operators' manufacturing performances and then investigates the factors that contribute to the functionalities of nudges. Results address that within the scope of the manufacturing assembly line task, despite nudges have collective impacts throughout the assembly task, the impact of nudges doesn't run constantly the same through the task duration, the power of nudges drops along the task and eventually hits zero (no impact) to the end. Moreover, the impact of nudges fluctuates as the assembly line tasks go on. After we zoomed in on the aspect of individual assembly task, we observed that human operators speeded up their paces on assembling the sequential part right after they received the nudges, the power of nudges only lasts for one part, and the subsequent task in the context of manufacturing assembly lines. The findings lead to the proposition of a design principle to construct a more reliable Industry 4.0 environment, which can be divided into two perspectives. From a collective perspective, attention needs to be paid to the time points for sending out nudges in manufacturing tasks, as the influence of nudges keeps decreasing as the tasks move on. It is deducted that information overload and monotonic tasks are two factors that formulate the time-related functionality of nudges. Each human operator got 3 times nudges throughout the entire manufacturing assembly process. When humans are subjected to an exceeding amount of information, their cognitive capacity can overwhelm them as a consequence, thus it's difficult to process and prioritize the important information they get. Additionally, since the assembly line tasks are repetitive, performing repeated tasks can also lead to desensitization to nudges. Human operators who are consistently exposed to the same duties may eventually become less receptive to the nudges. If we narrow it down to an individual task perspective, even though nudges benefit the overall manufacturing performances, the impact of nudges can be described as transient rather persistent, for nudges only function through consecutive task concerning individual human operator's manufacturing tasks. This finding triggers us to unbox the mechanism behind the scene. In this case, human fatigue is considered one important factor that contributes to the pattern-related functionality of nudges. When human operators are experiencing fatigue at work, it's difficult for them to keep focused on work nudges. Human operators' cognitive abilities can be compromised, and fatigue can impair their concentration. The other outcome that nudges generate can be contributed to the modalities they convey, which leads to the second research question on the differences of impacts caused by different modalities.

We categorize the modalities of nudges into two perspectives, the first is the sensorial modalities of carrier for nudges, which are auditory nudges, visual nudges, and somatic nudges. The other perspective is the sectoral level, which is the public level of nudges, aligned with auditory nudges and visual nudges, and the private level of nudges, which refers to somatic nudges. The second research question has brought forth the conclusion on how different modalities of nudges can affect human operators' manufacturing performances. Within the modalities (auditory, visual, and somatic/public, private) that are used to test in this study, somatic (private) nudges promote the cycle time values that human operators used to assemble, compared to the impact of auditory and visual (public) nudges, it is reasonable to infer that somatic (private) nudges are the optimal modality in contrast with auditory and visual (public) nudges. Different modalities of nudges grounds different distraction levels, humans' attention might be drawn away by auditory and visual disruptions.

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In conclusion, this study explores the application of nudges on human operators' manufacturing performances in manufacturing assembly lines. It is observed that the impact of nudges keeps diminishing throughout the assembly line task, the later the nudges were emitted, the weaker the power of the nudges is, and the nudges that were sent out at last has no impact on human workers' manufacturing performances. A detailed examination of the impact of each nudge revealed that nudges only function transiently, which means in this experimental study, human operators only accelerate the subsequent part after getting nudged, the cycle time values dropped at the subsequent part and went up again. Information overload, monotony, and human fatigue are the three major factors that determine how nudges function. Moreover, different modalities of nudges have different degrees of impact. Somatic nudges (private) were found to have a more significant impact than auditory (public) and visual (public) nudges. The distraction level of different modalities of nudges contributes to this finding.

Study limitations such as individual differences and levels of stress can lead to manufacturing performance differences. Human operators are different in their cognitive abilities, as a result, how well the manufacturing performances are, is dependent on how human operators attend to and process nudges. Meanwhile, it may be difficult for human operators to respond to nudges when they are experiencing stress. In the future, research on investigating the attributions of physiological manifestations should be conducted, such as putting biometric devices on participants to measure the physiological metrics, and to investigate the factors that impact humans' receptions of nudges accurately.

CHAPTER 5

CONCLUSIONS

To conclude the study, this chapter provides a brief review of the entire research. Practical implications, limitations, and future work are proposed for the next steps. We hope the protocol we proposed can serve as a cornerstone in the manufacturing research community.

5.1 Research Overview

With the rapid development of human-AI interaction in Industry 4.0, Understanding how AI implementation can influence human perception should be identified as a high priority since the implementation can modify human operators' manufacturing performances. However, prior studies have not thoroughly investigated the integration of both human implementation and AI system implementation synchronously, particularly with respect to exploring optimal interactions between the two components that the design of an AI system can trigger humans' behavioral changes. This study aims to investigate the effects of an AI-guided intervention referred to as "nudge" on human operators' manufacturing performances. Nudge is defined as a method of manipulating human perception through AI-guided intervention. By employing nudge as a communication media, this study examines the impact of nudge on human operators' manufacturing performances and evaluates whether nudge's modalities may also affect their performance. To achieve this, we devised a manufacturing assembly task to analyze the impact of nudges on human operators' manufacturing performance per the diverse modalities of nudges: auditory, visual, and somatic. The experiment involved 30 participants, with AI nudges presented to each participant through a notification device. The findings demonstrate that nudges significantly influence human operators ' manufacturing performance despite their short-lasting effects. Notably, the performance of nudges is influenced by factors such as information overload, task monotony, and human fatigue. Additionally, the study reveals that human operators exhibit varying manufacturing performance depending on the modalities of nudges. Somatic nudges outperform auditory and visual nudges in terms of improving manufacturing performance. Private nudges have a more substantial impact compared to public nudges. A qualitative analysis of operators' nudging experience is also provided. This study provides guidance for designing optimal human-AI interaction in advanced manufacturing processes in consideration of human factors.

Result shows that nudges affect human operators' manufacturing performances. It is also found that the impact of nudges does not persist until the end; the manufacturing performances showed oscillating patterns given the nudges. Nudge information overload, monotony of tasks and human fatigue are the factors contribute to the property of nudges. Changes in manufacturing performances also differ, given different modalities, which is caused by different distraction levels of nudges. This study discloses the identification and characterization of nudges. Lastly, we concluded this study with implications and future work recommendations.

Given the increasing focus on human-AI interaction within the Industry 4.0 landscape, it is of great importance to develop an understanding of how the implementation of AI can impact human perception and, consequently, alter the manufacturing performances of human operators. Our work facilitates the study of investigating the effects of a purportedly AI-guided intervention known as "nudges" on human operators' manufacturing performances within a mock manufacturing assembly line setting. In this context, the deployment of nudges is defined as a means of guiding human perception through AI-guided intervention. Through the use of nudges as an instrument, the study examines the impact of nudges on human operators ' manufacturing performances and evaluates how the modalities of nudges may impact their performances. The findings of the study reveal that nudges significantly impact human operators' manufacturing performances. Specifically, the study demonstrates that the impact of nudges does not persist until the end of the manufacturing process, and the performances exhibit oscillating patterns in response to nudges. The two factors that contribute to the time-related feature of nudges are information overload and monotony of tasks. Notably, the examination of each nudge highlights that nudges function in a transient manner, whereby human operators' performances only boosted in a limited duration of time. Human fatigue is a factor that is linked to the pattern-related characteristic of nudges. Finally, the changes in the manufacturing performances differ, depending on the modalities of the nudges employed, generated by various levels of distraction Somatic nudges perform better than auditory and visual nudges, and private nudges have a bigger impact than public nudges and combined (private and public) modalities of nudges.

Our study serves as a cornerstone for exploring the impact of AI on human behavior and, hence enhancing manufacturing performances. In doing so, this paper provides a framework for future research endeavors aimed at implementing human-AI interaction by designing effective nudge strategies with explicit information embedded to shape human operators' behavioral changes positively, thus optimizing manufacturing performances. Research on the components that sustain the effectiveness of nudges throughout the entire manufacturing assembly task holds significant promise. For each nudge, design strategies to standardize their impact are necessary. The importance of each modality is expected to be clarified with future studies, to determine if manufacturing performance is heavily influenced by the specific type of AI embodiment. From the standpoint of the affected group sector, it is also of great importance to examine if and how group nudges differ from individual nudges to better understand human-AI interaction in manufacturing environments. Finally, individual differences should be investigated through biometric measurements to gain deeper insights into the effects of nudges based on how human operators perceive them

5.2 Implications and Future Work

We developed an empirical equation that can be deployed to any CPSS, which is shown below in the finalized equation. This equation was developed based on the observation of the research experiment, and it is the fundamental equation generalized from CPSS framework, which can be adjusted and should be customized within the subject of different Industry 4.0 settings.

$$-\Delta T = \tau \, [C_N \, C_R \, log_b(N+1)] \pm \tau$$

Equation 1 Initial Empirical Equation

$$\Delta T = \tau(C_N \, C_R \, log_b(\frac{1}{N+1}) \pm 1) + sin\,(2\pi N)\, e^N$$

Equation 2 Finalized Empirical Equation

The final equation, shown above, encapsulates the relationship between manufacturing performance, the design of technological intervention, and human factors such as individual perception. ΔT, on the left side, denoted the change of manufacturing assembly cycle time. On the right side, C_N refers to the number of nudges that the participants received during the task, and this number can be modified regarding the design of the experiment. There exist scenarios when there are no nudges involved, then N should equal 0. Previous analysis in this research shows that the more nudges human receives the less effect the nudge has, thus, a diminishing return function is employed. From the social cues analysis, it is observed that human reception towards nudge signals varies, as C_R lies in the range of -1 to 1, where -1 represents human slowing down their working rate and 1 represents that human worker improved their working rate by reducing cycle time after getting nudged. If C_R equals 0, this means human operators ignore the nudge intervention. τ represents individual differences in manufacturing background and expertise, this parameter should also be justified in different organizations. Since this research only employs a limited number of nudges due to the experimental constraints, by adding $sin\ (2\pi N)$ to the equation, which represents more cycles of nudges, we can predict the future trends of ΔT, which is more applicable in real-world manufacturing settings. Finally, the dampening effect e^N makes the model accurate in predicting long-term behavior. Through this research, theoretical responses to nudge based on relevant and measurable worker response can be modeled, shown in the following figure.

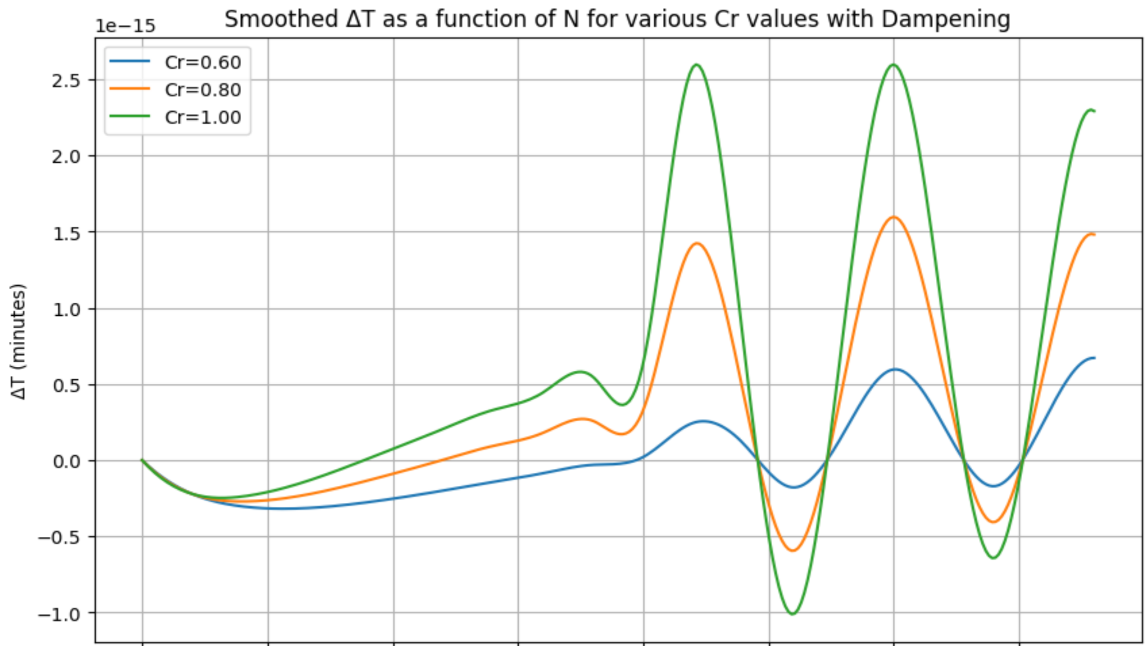

Figure 17 Theoretical Response for More Cycles

The practical implications of this research extend to several domains within human-AI interaction and manufacturing system design. From the perspective of cyber-physical system design, it is demonstrated that involving technological interventions with nudging functions can optimize factory production rates. In the realm of manufacturing and operational research, one key finding shows that the more nudges sent, the less effective they become. This implies that manufacturing companies should strategically distribute assembly tasks to avoid human operator fatigue from cognitive interventions. By quantifying relevant indicators such as individual background and manufacturing experience, organizations can develop new training systems to enhance workforce development. The integration of all aspects of this research has profound social implications, as it helps mitigate workforce-related issues by fostering a more responsive and adaptive workforce environment. This research provides a comprehensive framework for enhancing system design and operational efficiency while promoting human operator welfare.

Adopting a human-technology perspective to comprehend human-AI interaction helps to understand how technology can reshape the nowadays manufacturing systems by guiding human operators towards wanted manufacturing performances. It is important to employ the research from this perspective for the construction of Industry 4.0 requires higher adaptability and flexibility of human operator involvement and the application of technological assistance. This strategy strengthens the resiliency of CPSS while boosting the development of human and industry sectors [86]. It is emphasized in the previous research on the importance of enhancing collaboration between physical systems, software agents, and human operators in designing Industry 4.0 frameworks.

We suggest using AI-guided interventions that use explicit information to encourage human operators with positive behavioral changes, thus optimizing performance. Implication using the strategy could foster strong human-AI collaboration and human-robot collaborations [87]. Our experiment introduces a novel characterization of human-AI interaction through the theory of nudge within a simulated manufacturing environment, where nudges act as cognitive reminders.

This study proposed a methodological framework for future studies on human-AI interaction in Industry 4.0, incorporating both quantitative and qualitative approaches. Our research lays the foundation for examining AI's influence on human behavior from an interactive perspective. It is also recommended that future studies should explore various levels of human-AI interaction, both individually and in teams, to enhance human factors research in Industry 4.0 by investigating the underlying phenomenon of social cues in emerging human-AI dynamics. Research on elements that sustain the effectiveness of nudges throughout the entire manufacturing process holds promise. For each nudge, strategies to unify their impact are needed. The significance of each type is expected to be clarified with future investigations, determining if performance is highly dependent on the specific modality of AI application. It is crucial to study how group and individual nudges differ in their effects within manufacturing settings. Additionally, exploring individual differences by incorporating biometric measurements can provide deeper insights into how human respond to nudges.

Study limitations such as individual differences and level of stress can lead to manufacturing performances differences. Human operators are different in their cognitive abilities, as a result, how well the manufacturing performances are depend on how human operators attend to and process nudges. Meanwhile, it may be difficult for human operators to respond to nudges when they are experiencing stress. In the future, research on investigating the attributions of physiological manifestations should be conducted, such as putting biometric devices on participants to measure the physiological metrics, to investigate on the factors that impact humans' receptions of nudges accurately.

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