Technology Acceptance in the Manufacturing Environment

by

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Abstract

Employee technology acceptance is an important consideration for any manufacturing organization interested in implementing new technology in the workplace. Industry 4.0 introduces new technologies that can significantly impact manufacturing, but methods to ensure employees are prepared for implementation are lacking. Both individual and organizational-level acceptance are essential to consider. An organization can play a valuable role in preparing its employees for new technology before implementation, increasing the chances of a successful launch. This dissertation proposes a new tool for gauging employee technology acceptance in a pre-implementation decision context: the Technology Acceptance in a Manufacturing Environment (TAME) survey. TAME was developed by combining individual acceptance constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) with an organizational readiness construct adapted from the Organizational Readiness to Implement Change (ORIC) model (Shea et al., 2014). The validity of TAME was established through pilot testing in an academic environment and a broad experimental distribution among employees of a large automotive manufacturer with locations in both the Southeastern United States and Mexico. Content validity was confirmed via internal consistency measures and both expert panel and pilot participant feedback. Construct validity testing via confirmatory factor analysis for the UTAUT model as well as TAME was also supported using data collected from the employees of the automotive manufacturer. Lastly, non-parametric testing and structural equation models were developed using the manufacturer data to evaluate differences between groups and potential moderating variables. Results indicate that TAME is appropriate for assessing readiness for technology acceptance among manufacturing workers with little to no training or knowledge of the technology being considered for implementation.

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List of Abbreviations

AR	Augmented Reality
BI	Behavioral Intention
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CI	Confidence Interval
CPS	Cyber-Physical Systems
CR	Composite Reliability
DOI	Diffusion of Innovations
EE	Effort Expectancy
I4.0	Industry 4.0
IDT	Innovation Diffusions Theory
IoT	Internet of Things
IRB	Institutional Review Board
IS	Information Systems
KMO	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
M	Mexico
MM	Motivational Model
MOE	Margin of Error
MPCU	Model of Personal Computer Utilization
OR	Organizational Readiness
ORIC	Organizational Readiness to Implement Change
PE	Performance Expectancy

PEOU	Perceived Ease of Use
PU	Perceived Usefulness
RMSEA	Root Mean Square Error of Approximation
SCT	Socio-Cognitive Theory
SEM	Structural Equation Modeling
SI	Social Influence
SVP	Senior Vice President
TAM	Technology Acceptance Model
TAME	Technology Acceptance in a Manufacturing Environment
TOE	Technology-Organization-Environment
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
US	United States
UTAUT	Unified Theory of Acceptance and Use of Technology

Chapter 1. Introduction

1.1 Background

1.1.1 Manufacturing and Industrial Revolutions

Evidence of tools found in Kenya dates manufacturing as one of the oldest industries in existence (Harmand et al., 2015). As time has passed, manufacturing has evolved dramatically. There have been three documented industrial revolutions, each of which has produced significant changes in technological innovation and the manufacturing process (Rüßmann et al., 2015; Thoben et al., 2017). Industry 1.0 saw the invention of the power loom, revolutionizing fabric creation, and the advent of complex machines to replace manual tasks. Industry 2.0 was characterized by electrification and the development of mass production techniques, first seen in the “disassembly lines” of Cincinnati’s slaughterhouses. Industry 3.0 was marked by the computerization of manufacturing, often characterized by the introduction of robotics. Manufacturers began implementing automation and finding new uses for industrial robots that could complete tasks autonomously.

1.1.2 Industry 4.0

Industry is currently undergoing a fourth industrial revolution, primarily driven by a “demand for faster delivery times, more efficient and automated processes, higher quality and customized products” (Zheng et al., 2021). This revolution is defined by the progression from standalone automation to intelligent, integrated systems (Esmaeilian et al., 2016; Thoben et al., 2017). Technology has progressed to the point that it cannot only take over routine, otherwise manual tasks; it can also augment the human to increase capability and efficiency.

Germany coined the term "Industry 4.0" (I4.0) in 2011 and developed a government policy statement, “Industrie 4.0”, that codified the initiative in 2013. Since its introduction in

2013, the German government has presented I4.0 as an initiative to preserve Germany's position as one of the world's leading providers of advanced manufacturing solutions (MacDougall, 2014). I4.0 focuses on connecting innovative "embedded system production technologies and smart production processes to pave the way to a new technological age which will radically transform industry and production value chains and business models" (MacDougall, 2014). The German government, along with various universities and companies, presented the idea of "Smart Factories" integrated with Cyber-Physical Systems (CPS) and the Internet of Things (IoT). CPS uses advanced computational capability to combine the physical and virtual worlds and make the IoT possible. CPS are made possible through the evolution of computational capability, becoming more autonomous and advancing to the point that the physical and virtual worlds can be combined. The integration of the IoT into industry is what Germany termed "I4.0." Smart factories will utilize the IoT for networking all processes together into one cohesive platform, which allows for increased process flexibility and agile decision-making of the organization (Jung et al., 2017; Kagermann et al., 2013; Osterrieder et al., 2020; Thoben et al., 2017).

As I4.0 has progressed, the elements of a smart factory have evolved beyond the major concepts of CPS and IoT to include specific technologies (Erboz, 2017; Hermann et al., 2016; Mittal et al., 2016; Mittal et al., 2019; Thoben et al., 2017). The list of technologies associated with I4.0 and smart factories grows continually. For example, Mittal et al. (2016) first reported nineteen sub-technologies, then updated the number to thirty-eight in three years (Mittal et al., 2019). As the number and type of technologies grow, organizations must study what is available and how best to implement selected technologies (Armenakis & Harris, 2009). Not only can a flexible organization increase profitability (Biedenbach & Söderholm, 2008), but the ability to adapt can have a notable impact on short- and long-term success (Appelbaum et al., 2012). In short, organizations must evolve to survive (Hirschhorn, 2002). However, prior studies suggest the challenge and complexity of organizational change initiatives, with quantitative reports of up to an 80% failure rate (Higgs & Rowland, 2000; Hirschhorn, 2002; Knodel, 2004; Sirkin et al., 2005; Whelan-Berry & Somerville, 2010). This points to a significant need for research addressing this issue.

1.1.3 I4.0 Impact on Manufacturing

I4.0 is the first industrial revolution to be recognized in advance of its happening. This is different from the first three, which were only distinguished as industrial revolutions years after they had taken place (Kagermann et al., 2013; Thoben et al., 2017). This acknowledgement positions industry at an advantage for I4.0 implementation, provided the correct steps be taken in establishing the key contributors to the success or failure of an implementation effort.

Implementing I4.0 concepts can significantly impact integrating manufacturing processes and improving efficiency (Kagermann et al., 2013; Kinzel, 2017; Osterrieder et al., 2020; Rüßmann, 2015; Zheng et al., 2021). The IoT allows for the full integration of manufacturing systems and the creation of a Smart Factory where equipment, warehouses, and production facilities communicate with logistics, marketing, and service to create flexibility and increased visibility to the entire manufacturing process. In addition to optimizing existing processes, I4.0 has the potential to globalize visibility into the entire manufacturing enterprise and facilitate increased communication between suppliers and their customers and between employees (Kagermann et al., 2013; Yu et al., 2017). Rüßmann (2015) further predicts that I4.0 will lead to revenue growth, increased employment, and investment in the manufacturing industry.

In order to implement I4.0, certain technologies can be chosen based on the needs of the manufacturer. I4.0 technologies can be utilized in many manufacturing applications (Erboz, 2017; Esmaeilian et al., 2016; Rüßmann et al., 2015; Kamble et al., 2018; Osterrieder et al., 2020). Augmented reality (AR) can establish flexible parts-picking sequences and display part installation instructions to employees on the production line. 3D printing can create small batches, specialized parts. Big data allows the integration of multiple data collection systems for a holistic factory view and informed leadership decision-making. Cobots can make manufacturing processes safer and more ergonomic for employees. These examples are by no means exhaustive, and new I4.0 technology applications for manufacturing are identified continually.

1.1.4 Consideration for Human-Machine Interaction

As these new technologies continue to be developed and implementation begins, research supports the importance of human-machine interaction (Erboz, 2017; Kagermann et al., 2013; Neumann et al., 2021; Rüßmann et al., 2015; Thoben et al., 2017). Technology can assist people in doing their jobs by working with humans or working for humans. In working with humans, innovative technologies can enhance a human's job efficiency either physically (e.g., via an exoskeleton) or virtually (e.g., via AR as mentioned above, systems integration of a preventative maintenance schedule to alert technicians to imminent repairs, etc.) (Fantini et al., 2020; Romero et al., 2016, Ruppert et al., 2018). Alternately, technology can work for humans, where innovative technology replaces a task previously performed by a human. The evolution of technology applications has been instrumental in eliminating safety and quality concerns as well as allowing for the allocation of human resources to more high-level, skilled tasks (Esmaeilian et al., 2016; Kamble et al., 2018; Rüßmann et al., 2015; Thoben et al., 2017).

Research shows that increased technology adoption will net an increased number of jobs, albeit not the same jobs that existed before the technology was implemented (Rüßmann et al., 2015; Neumann et al., 2021). The I4.0 workforce must be prepared to take on jobs at a higher skill level or with a different skill set than what is needed for current manufacturing processes (Fantini et al., 2020; Rüßmann et al., 2015; Pfeiffer, 2016). Up to 90% of the post-I4.0 workforce may be semi-skilled labor with vocational training or other special qualifications. These individuals will maintain the automated systems to ensure quality and productivity are upheld (Pfeiffer, 2016). Although the foresight of I4.0 presents manufacturing an opportunity to prepare its workforce for the introduction of new technologies and increase skill level where necessary, manufacturers lack a clear method of technology selection and prioritization (Fantini et al., 2020; Jung et al., 2017).

1.1.5 The Role of an Organization in Technology Acceptance

Even at the earliest introduction of I4.0, it was acknowledged that there might be "technology acceptance issues" with the workforce (Kagermann et al., 2013). Sirkin et al. (2005) state that employees will resist taking on new responsibilities and changes outside their current work. A possible explanation is a lack of trust in the new technology. Alarcon et al. (2021) claim that until humans accept the new technology, the full benefit of it cannot be realized.

In the manufacturing context, the organization fosters technology acceptance in its employees (Rogers, 2003; Bouwman et al., 2005; Córdoba, 2009). In his work on the diffusion of innovations, Rogers (2003) theorized that the organization not only has a hand in individual acceptance, but that an individual depends on the organization to accept a new technology first. Bouwman et al. (2005) concur, writing that organizational leadership must support the adoption of new technology prior to acceptance by the individual.

1.1.6 Technology Acceptance in a Pre-Implementation Context

With leadership support, an organization may choose which technologies to onboard independent of individual input or seek input and feedback from potential users first (Bouwman et al., 2005; Córdoba, 2009). Although an organization may choose to implement new technologies without employee feedback, there is potential benefit in seeking user input prior to implementation. It would be helpful to determine the state of the technology acceptance disposition of employees before attempting to implement the technology. Suppose an organization can gauge employee acceptance before an implementation decision is made. In that case, it can provide additional information, training, or resources to curb potential concerns from employees about bringing new technology into the workplace. Additionally, potential users are often subject matter experts (Pfeiffer, 2016) and can provide input on the relevance of that technology to the application being considered. Furthermore, requesting employee feedback alone can garner support for a potential change (Sirkin et al., 2005).

The request timing of potential user feedback is important because organizations can gain the most unbiased insight at the earliest stages of the decision-making process. Venkatesh et al. (2003) pointed out that once participants are familiarized with a technology, acceptance or rejection has already occurred, and the decision-making window has closed. At this point, participants answer retrospectively (Fiske & Taylor, 1991; Venkatesh et al., 2000), and an accurate gauge of acceptance of new technology cannot be measured.

Suppose organizations want increased employee buy-in to avoid roadblocks in implementation efforts. In that case, they need to gauge employee acceptance of a new technology before investing significant resources in implementation. However, polling employees in a pre-adoption stage requires them to provide feedback without a working knowledge, training, or use of the technology, i.e., a “true” pre-implementation context. Therefore, "pre-implementation" is defined as a pre-decision context where participants have no working knowledge or training on the technology being studied.

1.1.7 I4.0 Research & Limitations

Reports in the literature indicate that manufacturers need to gauge employee acceptance of a new technology prior to significant resource investment in implementation. Despite these findings, the bulk of I4.0 research focuses on the operational capabilities, integration with other compatible systems, and efficiency or informational gains of the technologies rather than the human component of I4.0 (Kamble et al., 2018; Kinzel, 2017; Neumann et al., 2021). A recent literature review on I4.0 research found that only 12.3% of the papers addressed human-machine interaction (Kamble et al., 2018). Further, even in studies on human-machine interaction, the focus is often on the capacity of the human for a particular technology (Fantini et al., 2020; Romero et al., 2016, Ruppert et al., 2018) with no consideration of human factors or outside influences on the user that may affect their experience (Neumann et al., 2021). Given the prediction that the workforce will increase with I4.0 implementation (Rüßmann et al., 2015), research should be focused on how to integrate I4.0 technologies into the assembly process and how to ensure the workforce is prepared to interact with these new technologies.

1.1.8 Background Summary

The possibility of increased revenue through efficiency gains and the ability to address important environmental and safety concerns has put the need to adopt new technologies at the forefront of manufacturers’ concerns (Esmaeilian et al., 2016; Kamble et al., 2018; Rüßmann et al., 2015; Thoben et al., 2017). Zheng et al. (2021) proposed that I4.0 may most impact manufacturing due to the number of areas technology may be implemented for efficiency gains.

There are several important considerations in new technology implementation. First, the organization must consider the human factors component of implementation, not just the possible efficiency gains of new technology (Erboz, 2017; Kagermann et al., 2013; Neumann et al., 2021; Rüßmann et al., 2015; Thoben et al., 2017). Second, the organization's readiness must be prioritized, as it has been theorized that organizations directly influence employees' level of acceptance of new technology (Rogers, 2003; Bouwman et al., 2005; Córdoba, 2009). Third, organizations should test employees' acceptance levels before making an implementation decision. Employee input is valuable (Pfeiffer, 2016), may provide a morale boost (Sirkin et al., 2005), and ensures that employees are giving feedback prior to a personal acceptance or rejection decision (Venkatesh et al., 2003). It also reduces the likelihood of the organization investing resources into an implementation effort that is delayed or fails due to a lack of employee support.

With the above considerations in mind, there is a clear need for organizations to gauge the technology acceptance of their workforce prior to new technology implementations. This gauge will give organizations insight into whether their workforce accepts a new technology before launch and allow them to better prepare the workforce before beginning the implementation process. Without first determining gaps in readiness, attempts to implement may be unnecessarily challenging or even fail, creating uneasiness toward technology adoption and sending the company backward in its goals (Kotter, 1996).

1.2 Dissertation Organization

This dissertation includes seven chapters. The organization is as follows: Chapter 1 introduces the research topic, background and related literature, purpose, and research goals. I4.0 and its impact on the manufacturing domain are discussed as well as key factors contributing to the success or failure of I4.0 technology implementation. A need for a way to measure the technology acceptance of a manufacturing workforce prior to the implementation of a new technology is established. Chapter 2 summarizes the literature related to existing technology acceptance models. Both individual and organizational technology acceptance models are discussed, with the benefits and drawbacks of each. Chapter 3 introduces the problem statement and need for a model for manufacturing use in a pre-implementation context that combines constructs from individual and organizational acceptance models. Objectives of the research and accompanying hypotheses are also outlined. Chapter 4 details the methodology used to study the topic. This includes participant and sample selection, a detailed review of survey development, and pilot and full-scale phase deployment. The pilot phase intends to confirm the survey's structure and test the instrument's feasibility, and the full-scale phase applies the model to the target population to test research hypotheses. Modifications to the survey instrument for the pilot and full-scale phases are discussed, and the selection process of statistical validation methods for the full-scale phase is included. Chapter 5 is a detailed review of all exploratory and confirmatory testing and validation of the data. Each test outlined in the Methods chapter is applied where appropriate, and results are reported. Chapter 6 discusses key findings from phase, achieved objectives, and the theoretical basis for setting up overall conclusions. Chapter 7 includes a summary of conclusions reached, study limitations, and future research opportunities.

Chapter 2. Literature Review

2.1 Gauging Technology Acceptance

Research into I4.0 and new technology implementation support manufacturers' need to gauge employee readiness to interact with new technologies. One way to do this is by pairing a model with an accompanying survey instrument. To build a model to test technology acceptance, one must understand all potential factors related to whether or not a person intends to utilize available technology. These factors can be arranged into the model and studied in combination to determine the significance of interactions. Once relationships between factors are understood, organizations can obtain employee feedback and address gaps to prevent unnecessary setbacks in the implementation process.

2.1.1 Individual Technology Acceptance Models

Several technology acceptance models currently exist in the literature. Many of these models aim to gauge opinions, feedback, and overall acceptance levels of the individual as an isolated entity from the organization and in a post-implementation context. The following subsections summarize existing technology acceptance literature on models targeting the individual.

2.1.1.1 The Technology Acceptance Model

In 1989, Davis introduced the Technology Acceptance Model (TAM; Figure 1). Davis (1989) derived TAM from Fishbein & Ajzen’s (1975) Theory of Reasoned Action (TRA), which posits that an individual’s decision to act comes from intent, and that intent to act is dependent upon the attitude and expected outcome of the action.

Davis (1989) proposed two main factors driving technology acceptance, perceived usefulness (PU) and perceived ease of use (PEOU). PU is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance," and PEOU is defined as "the degree to which a person believes that using a particular system would be free of effort." Davis (1989) theorized that the more strongly a person believes a given technology will help him or her complete a task, the higher the chance of acceptance. Additionally, the easier a given technology is to use, the higher the chance of acceptance. Testing the model showed that PEOU predicated PU and confirmed that both affect behavioral intention (BI) to use a specified technology (Davis, 1989).

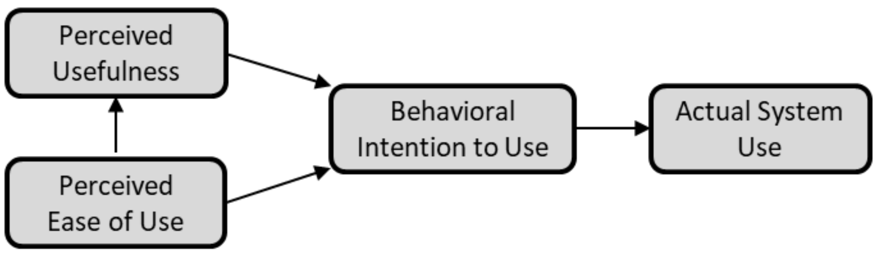

Figure 1. TAM (Davis, 1989)

TAM provided the basis for much of the later technology acceptance literature. However, TRA and TAM do not consider one important factor: the decision to act can be affected by the individual's intention and other factors outside that person's control (Sheppard et al., 1988). TRA and TAM are not robust enough to incorporate all necessary factors in today's manufacturing environment. Additionally, some researchers have claimed that the many iterations of TAM confuse the body of research on technology acceptance and prevent researchers from determining which version is optimal (Benbasat & Barki, 2007).

2.1.1.2 Unified Theory of Acceptance and Use of Technology

In recognition of the growing varied body of research on technology acceptance, Venkatesh et al. (2003) sought to consolidate the various available models into one cohesive construct. They first identified eight models primarily used in technology acceptance literature, as summarized in Table I. They then conducted four studies to test the relationships between all constructs in these eight models and consolidated all unique factors. These unique factors were tested in two additional studies and further synthesized based on the results. The resulting survey instrument and model were termed the Unified Theory of Acceptance and Use of Technology (UTAUT), with four key factors affecting user acceptance (Venkatesh et al., 2003).

In UTAUT, the first key factor of acceptance is performance expectancy (PE), defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). This metric is similar to PU in TAM as well as the following other variables described in the technology acceptance literature: extrinsic motivation (Davis et al., 1989 & 1992), job fit (Thompson et al., 1991), relative advantage (Davis et al., 1989; Moore & Benbasat, 1991; Plouffe et al., 2001), and outcome expectations (Compeau & Higgins, 1995; Davis et al., 1989). Like Davis (1989), Venkatesh et al. (2003) found that performance expectancy significantly impacted behavioral intention.

Effort expectancy (EE), the second factor included in UTAUT, is defined as "the degree of ease associated with use of the system" (Venkatesh et al., 2003). This metric is an adaptation of PEOU in TAM and is similar to factors defined in other acceptance models, such as complexity and ease of use (Davis et al., 1989; Moore & Benbasat, 1991; Plouffe et al., 2001; Thompson et al., 1991). Effort expectancy is thought to be especially key in introducing new technology and becomes less significant as time goes on and users become more familiar with the technology (Davis et al., 1989; Szajna, 1996; Venkatesh, 1999). This makes effort expectancy of particular interest and provides evidence that potential users should be surveyed prior to any experience or training with new technology.

Table I. Technology Acceptance Models

Model	**Independent Constructs**
Theory of Reasoned Action (TRA; Fishbein & Ajzen, 1975)	• Attitude: individual’s feelings about performing the behavior • Subjective Norm: influence from others who are important to an individual
Technology Acceptance Model (TAM; Davis, 1989)	• Perceived Usefulness: whether an individual feels that a given technology will help him or her do the intended job better • Perceived Ease of Use: whether the technology is easy to use
Motivational Model (MM; Davis et al., 1992)	• Extrinsic Motivation: the possibility of achieving objectives unrelated to the behavior (for example, a promotion) • Intrinsic Motivation: some unknown factor related to performing the behavior itself
Theory of Planned Behavior (TPB; Ajzen, 1991)	• Attitude • Subjective Norm • Perceived Behavioral Control: how easy it is to perform a behavior
Combined TAM/TPB (Taylor & Todd, 1995)	• Attitude Toward Behavior • Subjective Norm • Perceived Behavioral Control • Perceived Usefulness
Model of PC Utilization (MPCU; Thompson et al., 1991)	• Job-fit • Complexity • Long-term Consequences • Affect Towards Use: similar to attitude • Social Factors: similar to subjective influence/norm • Facilitating Conditions: environmental factors affecting use
Innovation Diffusion Theory (IDT; Moore & Benbasat, 1991; adapted from Rogers, 2003)	• Relative Advantage: the iterative improvement from the last version of that technology • Ease of Use • Image: social status related to use • Visibility: prevalence of use within the organization • Compatibility: consistency with needs and previous experiences • Results Demonstrability: the ability to see and communicate performance of the technology • Voluntariness of Use: the ability to choose whether or not to use it
Social Cognitive Theory (SCT; Compeau & Higgins, 1995)	• Outcome Expectations – Performance • Outcome Expectations – Personal • Self-efficacy: individual perception of ability to use the technology • Affect • Anxiety

The third factor in the UTAUT model is social influence (SI), defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). In other models, this metric is called subjective norm or social norm. This metric describes the impact of the perception of other people whose opinions the user values. Research has shown social influence to be insignificant in voluntary settings but significant in mandatory settings (Hartwick & Barki, 1994; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Findings suggest this may be due to a user wanting to meet the expectations of someone who can reward or punish him or her (French & Raven, 1959; Warshaw, 1980). In manufacturing, social influence may play a role in user technology acceptance for a few reasons. First, employees are often part of a team of peers who are also faced with the decision to accept new technology. Opinions of these peers could influence individual adoption. Additionally, potential users have a boss – or even multiple management members–who may influence individual acceptance. Lastly, whether the organization, typically about high-level leadership or decision-makers, wants an individual to use technology may influence acceptance.

The final primary factor in UTAUT is facilitating conditions (FC). Facilitating conditions describe "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003). While performance expectancy, effort expectancy, and social influence have all been found to predict behavioral intention, the facilitating conditions construct differs in predicting actual use. Therefore, it is possible that the information gained by including facilitating conditions as a separate factor is more indicative of whether or not a user is feasibly able to use a given technology with the resources at hand, outside of whether that person wants to use it or not.

As shown in Figure 2, each of the four main factors of UTAUT is moderated by some combination of gender, age, experience with the technology, and voluntariness of use. This information can be useful to an organization when looking at employee demographics. For example, an organization will know that an employee's age can affect that person's intention to use or actual use capability of a new technology. With this knowledge, the organization can provide additional resources to older (or younger, depending on the direction of moderation) employees to potentially increase their level of technology acceptance.

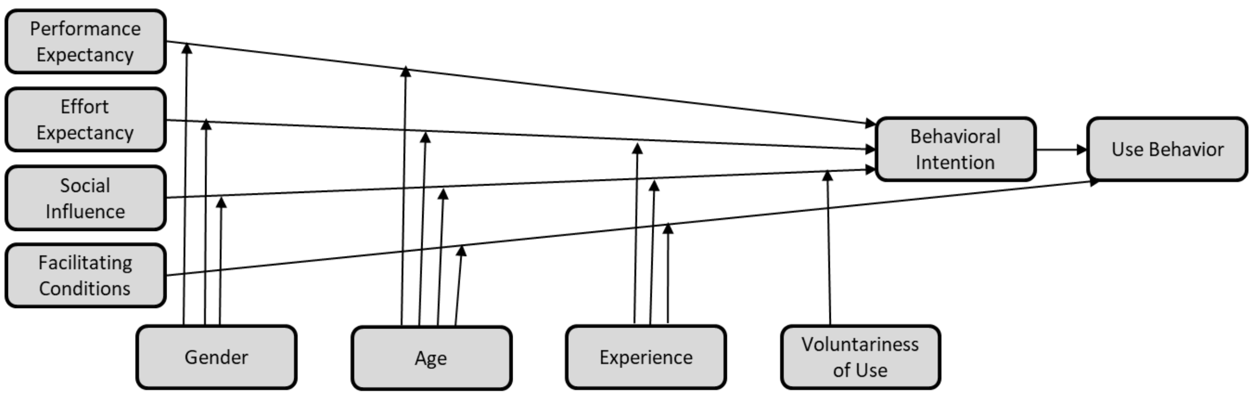

Figure 2. UTAUT (Venkatesh et al., 2003)

It is important to note which factors from other technology models were not included in UTAUT. These factors are either not determinant of behavioral intention and/or use or are fully encompassed by one of the four factors described above (Venkatesh et al., 2003). These include self-efficacy, anxiety, and attitude, which are mediated by PEOU, and, therefore, effort expectancy (Venkatesh, 2000).

2.1.2 Organizational Technology Acceptance

Although UTAUT has been shown to adequately predict the acceptance levels of an individual (Venkatesh et al., 2003), it lacks an influential factor for the manufacturing industry: the organization. Bouwman et al. (2005) define an organization as “a unit of formal positions, usually held by individuals, with explicit objectives, tasks, processes and assets.” A key to this definition is that individuals working within the organization may not have the same objectives as the organization, which complicates successful goal achievement (Bouwman et al., 2005). As outlined in Section 1.1.5, any technology acceptance model applied to manufacturing must consider the organization's role in an employee's technology acceptance. Several organizational technology acceptance models exist in the literature that may be utilized in the development of a model combining both individual and organizational factors, including the Technology-Organization-Environment (TOE) method (Tornatzky et al., 1990), Diffusion of Innovations (DOI; Rogers, 2003), and the Organizational Readiness to Implement Change (ORIC) model (Shea et al., 2014).

2.1.2.1 Technology-Organization-Environment Method

Tornatzky et al. (1990) introduced the TOE method, which considers various organizational components of technology acceptance (Figure 3). The three factors of technology adoption in the TOE model are technological context, organizational context, and environmental context (Baker, 2012). The technological and environmental contexts contain metrics that may be relevant to a decision-maker or provide information to establish a business case for a certain technology but do not capture the opinions of working-level employees who will be the ones interacting with that technology. However, the organizational context contains some elements that may be relevant at the individual employee level.

TOE proposes several sub-factors within the organizational context metric. First, links between cross-functional groups that promote benchmarking and cross-deployment improve the organization's likelihood of adopting and implementing new technology (Galbraith, 1973; Tushman & Nadler, 1986). Organizations emphasizing teamwork, communication, and "fluidity in responsibilities for employees" are more successful technology adopters (Baker, 2012). It makes sense then that effective communication from management to working-level employees has also improved technology adoption. Members of management who encourage a culture of change and innovation can positively affect employees' views on technology adoption (Tushman & Nadler, 1986).

Other proposed sub-factors within the organizational context are slack and size, but each of these metrics has some contradiction in the literature. Organizational slack, or the excess resources maintained by an organization beyond operational necessity, has been shown to increase (March & Simon, 1958; Rogers, 2003) and do not affect (Tornatzky et al., 1983; Tornatzky et al., 1990) technology adoption. The size of an organization may also improve chances of adoption (Cyert & March, 1963; Kamien & Schwartz, 1982; Scherer, 1980), but research has questioned this conclusion due to the possibility of confounding factors like resource availability at larger organizations (Kimberly, 1976). This has led to calls for the variable "size" to be broken out and studied in sub-components (Baker, 2012).

A further limitation of TOE in its applicability to a technology acceptance model for employees is its focus on general organizational "characteristics and resources" rather than individuals' perceptions in a workgroup (Baker, 2012). Documented communication procedures and other quantifiable metrics (e.g., slack, size) may be important considerations but are not direct measures of employee perceptions of the organization's readiness.

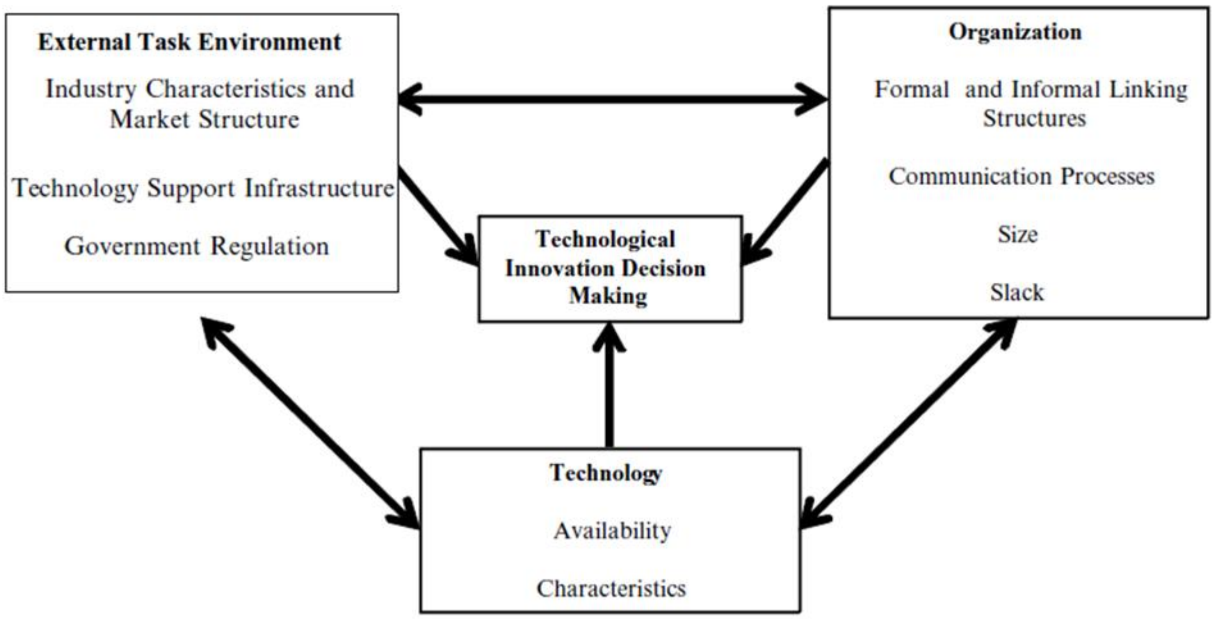

Figure 3. TOE (Tornatzky et al., 1990)

2.1.2.2 Diffusion of Innovations Theory

The DOI theory proposed by Rogers (2003) provides a model with individual and organizational factors (Figure 4). The DOI theory states that five primary factors contribute to the acceptance of an innovation: rate of adoption, relative advantage, compatibility, complexity, trialability, and observability. The adoption rate refers to how quickly members of an organization adopt an innovation, including the type of innovation decision, level of communication at each level of innovation decision, culture, and change agents' support and effort in diffusion. Relative advantage describes the perception that an innovation is better than its previous version. Compatibility is the level to which the innovation is perceived to line up with existing values and experiences. Complexity is the degree of difficulty potential adopters expect. Trialability is the ease of experimenting with an innovation. Observability is the ability of individuals to observe the results of an innovation. The model classifies the level of acceptance into five stages: knowledge, persuasion, decision, implementation, and confirmation.

It also classifies potential adopters into innovators, early adopters, early majority, late majority, and laggards (Rogers, 2003). Some of these concepts were applied to UTAUT when synthesized with other models.

In addition to his theory on innovation and individual technology acceptance, Rogers (2003) also provides a model for organizational innovativeness. He posits that organizational innovativeness is based on three main factors: individual (leader) characteristics, internal characteristics of the organizational structure, and external characteristics of the organization. Individual characteristics refer to leadership and company decision-makers' attitudes toward adopting innovations. The "external characteristics of the organization" metric refer to system openness, or the ability of a system to be altered by outside sources. Internal characteristics of the organizational structure include centralization, complexity, formalization, interconnectedness, organizational slack, and size. Definitions are as follows:

- Centralization: "the degree to which power and control in a system are concentrated in the hands of a relatively few individuals"
- Complexity: "the degree to which an organization's members possess a relatively high level of knowledge and expertise"
- Formalization: "the degree to which an organization emphasizes its' members following rules and procedures"
- Interconnectedness: "the degree to which the units in a social system are linked by interpersonal networks"
- Organizational slack: "the degree to which uncommitted resources are available to an organization"
- Size: "the number of employees of the organization"

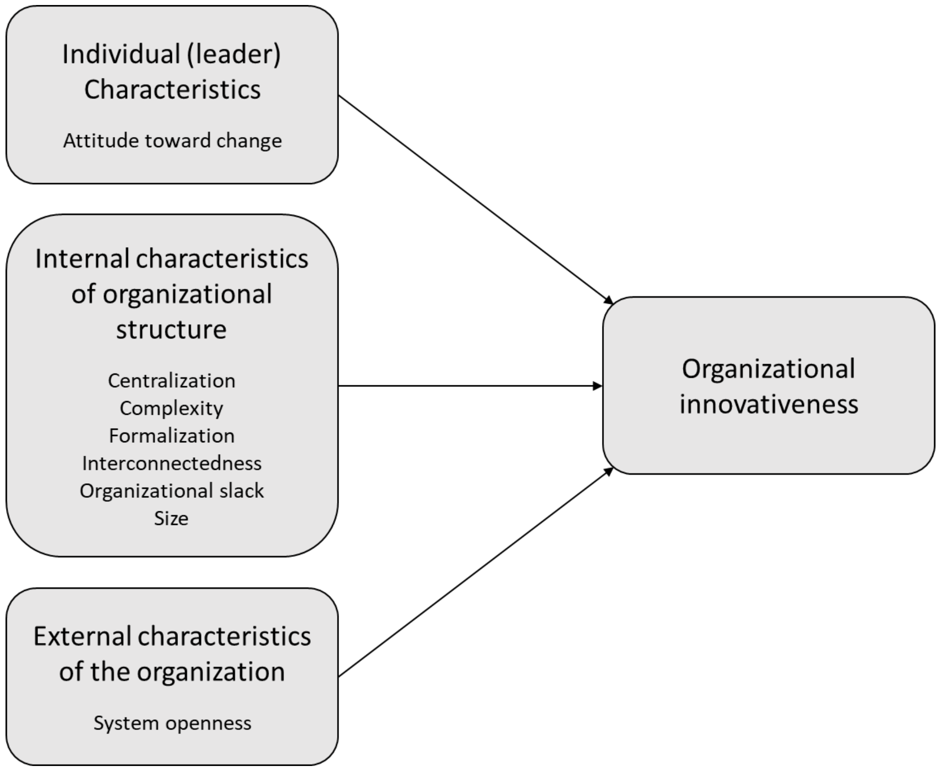

Figure 4. DOI (Rogers, 2003)

The DOI theory has been utilized to marry behavioral characteristics with the technical aspects of previous theories such as TOE. Baker (2012) claims that DOI and TOE share nearly identical factors. However, DOI has the same drawbacks as TOE in that it utilizes organizational metrics to quantify readiness rather than measuring employee perception of DOI as a standalone model. DOI does not encompass all relevant aspects of individual technology acceptance that must go along with the organizational component and focuses primarily on leader (i.e., decision maker) feedback. It is important to consider feedback from the organization's decision-makers, as they can choose which technologies to implement. However, once a technology has been chosen by leadership, it is also important to consider the opinions of employees who will implement and interact with it. This is key to successful implementation because individual employee perceptions and the organization may differ (Bouwman et al., 2005), which can cause setbacks in implementation efforts (Kotter, 1996).

2.1.2.3 Organizational Readiness to Implement Change Model

In 2014, Shea et al. introduced the ORIC model (Figure 5). This model is based on Weiner's 2009 theory of organizational readiness for change in which he introduces two metrics: change commitment, which "refers to organizational members' shared resolve" to actively make changes, and change efficacy, which "refers to organizational members' shared beliefs in their collective capabilities" to make changes. In developing his theory, Weiner (2009) recognized that technology acceptance research must extend beyond individual acceptance and incorporate the organization, as "organizational readiness for change is a multi-level, multi-faceted construct."

Shea et al. (2014) extended this theory to a testable model. Of the currently available organizational technology acceptance models, ORIC reaches beyond organizational metrics (i.e., size, slack, technological capability) and is intended for employee feedback. In ORIC, change commitment and change efficacy are preceded by two items. The first is change valence, or the value placed on change within an organization, and the second is an informational assessment of task demands, resource perceptions, and situational factors. The level of change commitment and efficacy is thought to be directly applicable to change-related effort, including initiation, persistence through implementation, and cooperative behavior across the organization (Shea et al., 2014). These constructs were shown to be a good measure of organizational technology acceptance culture.

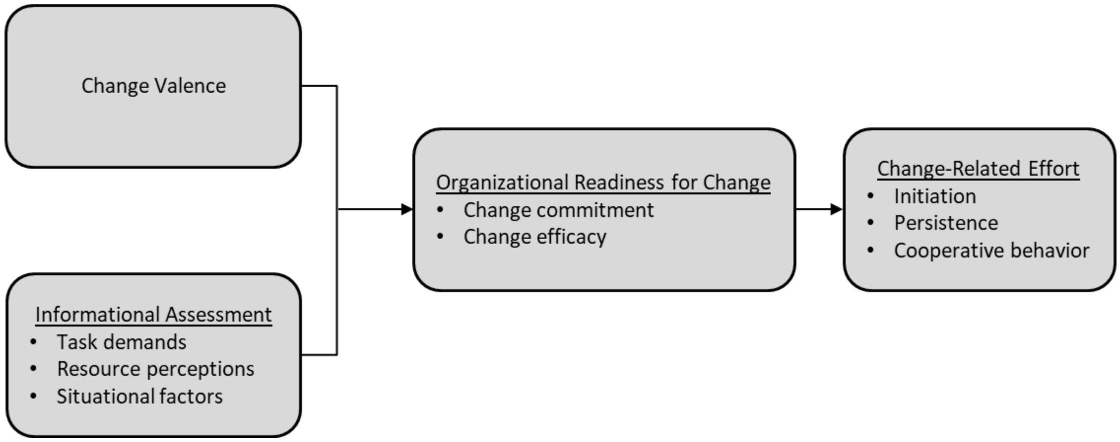

Figure 5. ORIC (Shea et al., 2014)

2.2 Limitations of Technology Acceptance Models

Existing technology acceptance models are an excellent foundation to grow from but do not encompass all the needs of a manufacturing environment. One primary limitation of technology acceptance models is a lack of focus on the pre-implementation context. Existing models were not developed for a true pre-implementation context, and survey instruments are worded in a mixed pre- and post-implementation context or a post-implementation-only context. Studies applying individual technology acceptance models have been primarily conducted in current-use contexts or in situations where participants were familiarized with the system prior to the survey and/or given the opportunity to try systems firsthand (Davis, 1989; Venkatesh et al., 2003). Even in studies with non-users, often the participants are individual consumers who have already made a use decision or employees who have prior familiarity with the technology being studied (Loo et al., 2009; Tavares & Amarel, 2010; Whitten et al., 2009). While this approach is generally accepted in the literature, there is a need to understand participant acceptance toward a specified technology with only a brief introduction for awareness before any significant knowledge gain or training is needed. Once knowledge gain occurs, participants have already decided whether or not they wish to use the new technology (Venkatesh et al., 2003), and the opportunity to obtain feedback while participants may still be open to the idea of the new technology has passed (Fiske & Taylor, 1991; Venkatesh et al., 2000). Surveying employees prior to significant knowledge gain ensures an unbiased, pre-decision measurement of technology acceptance when the organization has not yet invested significant resources into implementation.

Another limitation is the context in which technology acceptance models have been applied. Early technology acceptance models were developed for testing information systems and for technologies like email, fax, and other office software. Venkatesh et al. (2003) expanded the application of a technology acceptance model to an online database, meetings, and analysis software, but there was no application to manufacturing-relevant technologies. Environments studied include information systems (IS), government, commerce, education, and health (Attuquayefio & Addo, 2014; Williams et al., 2015). However, there has been limited manufacturing application (Abu, 2016; Adam et al., 2011; Suhendra et al., 2009), with no application to large-scale manufacturers.

Even if applied to manufacturing, not one of the current individual technology acceptance models includes an understanding of the organizational readiness to implement new technology. All of the models are intended for an individual, and many are targeted to an individual consumer, not part of an organization. Constructs such as perceived usefulness, ease of use, and social influence are geared toward psychological aspects of human decision-making. These constructs are important considerations in technology acceptance. However, the literature suggests that individuals who are a part of an organization can be influenced by the organization itself when considering the use of new technology (Bouwman et al., 2005; Córdoba, 2009; Rogers, 2003). Standard processes define manufacturing organizations, and individual employees likely will not have the final choice in whether a technology will be implemented on their jobs. Instead, employees will only have control over their reaction to the technology. If employees do not accept it, implementation will be much more challenging for the organization (Kagermann et al., 2013; Sirkin et al., 2005). Due to the potential challenges employees can introduce in implementation efforts, it is important to gauge their level of acceptance in advance, including their perceptions of the organization's readiness to implement new technologies. This allows an organization to address concerns and increase acceptance before significant resource investment. Therefore, for a technology acceptance model to be appropriate for a manufacturing context, it should include a measurement to account for employees' perception of the organization's readiness.

Organizational acceptance models primarily focus on the technologies and the organization's capabilities (Rogers, 2003; Tornatzky et al., 1990), but not the individual employee. They are instead geared toward the organization as a whole and considerations of decision-makers (Baker, 2012). Current organizational acceptance models also do not contain individual acceptance constructs (Davis, 1989; Venkatesh et al., 2003) and depart from human factors principles that value individual perspectives.

2.3 Technology Acceptance Summary

Manufacturers need a way to gauge employee acceptance of a new technology before implementation. Several models intending to measure technology acceptance have been introduced. One of the first technology acceptance models was TAM (Davis, 1989). This model introduced the idea that perceived usefulness (i.e., the potential benefits one expects from using the proposed technology) and perceived ease of use (i.e., the anticipated user-friendliness of the proposed technology) were significant contributors to acceptance. Several derivative models were introduced and independently validated over the years.

Venkatesh et al. (2003) made a significant contribution to the field of technology acceptance research by conducting a thorough literature review on eight different technology acceptance models and consolidating the most significant aspects of each into their UTAUT model. UTAUT proposes four key factors affecting user acceptance. The first key factor of acceptance is performance expectancy, defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance." The second key factor is effort expectancy, defined as "the degree of ease associated with use of the system." The third factor is social influence, defined as "the degree to which an individual perceives that important others believe he or she should use the new system." The final primary factor in UTAUT is facilitating conditions, which describes "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003).

In addition to technology acceptance models measuring an individual, there are also models with an organizational component. In 2014, Shea et al. introduced ORIC. ORIC is based on Weiner's (2009) theory of organizational readiness for change in which he introduces two metrics: change commitment, which "refers to organizational members' shared resolve" to make changes actively, and change efficacy, which "refers to organizational members' shared beliefs in their collective capabilities" to make changes. These constructs were shown to be a good measure of organizational technology acceptance.

Each individual and organizational technology acceptance model has unique benefits and common drawbacks related to the presence or absence of specific constructs being studied.

Individual acceptance models do not have a component gauging employees' perception of the organization's readiness, which can impact their acceptance (Rogers, 2003; Bouwman et al., 2005; Córdoba, 2009). Organizational models focus too much on technology specifications and construct relevant to the decision-makers, not individual employees.

However, all currently proposed models share some disadvantages. First and most importantly, these models have been primarily applied in current or post-use contexts, with minimal consideration for pre-implementation contexts. This is despite support for greater implementation success if employees buy into the change before launch (Kotter, 1996). Additionally, technology acceptance models have been primarily applied to non-manufacturing contexts, providing little support for their use in the manufacturing industry. Lastly, neither individual nor organizational technology acceptance models encompass all relevant factors that must be considered for the manufacturing domain.

Chapter 3: Research Statement

3.1 Conceptual Framework

A literature search into available technology acceptance models revealed that currently available models primarily focus on the individual or the organization, but not both. These models have been applied mainly in current or post-use contexts, with minimal consideration for pre-implementation initiatives. Technology acceptance literature has also not been widely applied to manufacturing and is even more limited in application to large-scale manufacturing enterprises.

The project described in this dissertation aims to determine technology acceptance factors that apply to a pre-implementation manufacturing context. Through a literature search on technology acceptance, a variety of models addressing different scenarios was discovered. UTAUT was found to be the most appropriate model to use as a base because it is a validated, widely used synthesis of eight previously existing technology acceptance models addressing individual perceptions regarding a specific technology (Venkatesh et al., 2003).

In developing UTAUT, Venkatesh et al. (2003) attempted to address five key concerns with existing technology acceptance models: type of technology, participant type, level of experience with the technology, type of study, and voluntariness of use. However, Venkatesh et al. (2003) did not test UTAUT in a manufacturing setting. The instrument was formulated as a current or post-implementation design, and the model does not include an organizational factor. Support for organizational influence in the success or failure of new technology implementation (Kotter, 1996; Rogers, 2003; Bouwman et al., 2005; Córdoba, 2009) points to a need for a technology acceptance model encompassing both individual and organizational constructs relevant to manufacturing environments.

3.2 Research Questions and Objectives

Manufacturing organizations need a way to gauge their employees' technology acceptance before implementing new technology. The need exists for a model applicable to I4.0 technologies in a pre-implementation context and encompasses the human component of technology acceptance, including both individual and organizational characteristics. Based on the current literature, no existing technology acceptance model fully encompasses the needs of a manufacturing organization intending to gauge the technology acceptance levels of its employees prior to new technology implementation. Considering these findings, the current project aims to:

1. Create a technology acceptance model with applicability to a large-scale manufacturer in a pre-implementation context.
    - H_0: Constructs in the UTAUT model, with survey items modified to a pre-implementation context, sufficiently measure the technology acceptance of employees in a manufacturing organization.
    - H_1: Constructs in the UTAUT model, with survey items modified to a pre-implementation context, do not sufficiently measure the technology acceptance of employees in a manufacturing organization.
2. Determine whether the perception of the organization's readiness affects technology acceptance for individual employees.
    - $H_{0'}$: Adding a pre-implementation organizational readiness (OR) construct to the pre-implementation UTAUT model (measuring individual acceptance only) has no impact on the ability to predict technology acceptance of employees in a manufacturing environment.

- $H_{1'}$: Adding a pre-implementation OR construct to the pre-implementation UTAUT model increases the ability to predict the technology acceptance of employees in a manufacturing environment.

3. Determine whether there are gaps in acceptance between various departments (i.e., front-line workers and engineering) or locations of the same employer.
    - $H_{0''}$: Technology acceptance of manufacturing employees in a pre-implementation context is the same across sample groups.
    - $H_{1''}$: There are differences in the level of technology acceptance of manufacturing employees in a pre-implementation context across sample groups.

This research addresses these objectives through the following:

- Validation of UTAUT in a pre-implementation manufacturing context
- Addition of organizational readiness (OR) component to a pre-implementation UTAUT model
    - Comparison between UTAUT and proposed model results to determine the best fit for a manufacturing environment
- Comparison between responses in various departments of manufacturing and levels of management

An applicable technology acceptance model for pre-implementation initiatives in the manufacturing environment would provide manufacturers and their employees with a tool to implement technology more efficiently and effectively. This model would begin laying the roadmap for manufacturers to implement I4.0 technologies, which are needed in the industry.

Chapter 4: Methodology

4.1 Introduction

The following chapter presents the Methodology associated with developing a technology acceptance model for pre-implementation in the manufacturing environment. A participant type and selection summary is presented, followed by sampling strategies and sample size calculation. Specific methodology for the pilot and full-scale phases are then reviewed, including measurement instrument development. These studies utilize a cross-sectional survey design, which is intended to assess technology acceptance in a pre-implementation context.

4.2 Participants

The population of interest is manufacturing employees who may help implement or use an I4.0 technology in their workplace. Two different sampling methods were used for the pilot and full-scale phases. A sample of graduate students interested in technology innovation in manufacturing was recruited for the pilot phase to increase the potential of survey participants having a basic concept of how new technologies may apply to the manufacturing domain. As this preliminary study phase was not intended to draw statistical conclusions about technology acceptance, a target sample size was not calculated.

4.3 Sample Size

An adequate sample size is needed to ensure that collected data is representative of the target population (Henry, 1990; Kish, 1965). Failure to obtain an adequate sample size can cause inaccurate results (Laumann et al., 1994; Mosteller, 1949). Although larger sample sizes can lead to more representative data, there have been some reports that low response rates compared to the total population do not necessarily lead to error (Krosnick, 1999; Visser et al., 1996). Instead, several methods have been suggested to calculate appropriate sample sizes depending on the target population.

An adequate sample size was calculated to draw statistical conclusions about the target population to ensure data reliability. There are many methods for determining adequate sample size, and there is not one correct way to do so (Bartlett et al., 2001). However, Cochran (1977) introduced a sample size calculation formula that is widely used and generally accepted in the literature. The sample size calculation formula is as follows:

$$\text{Sample size} = \frac{Z^2 \times \sigma \times (1- \sigma)}{\text{MOE}^2}$$

Where,

- Z = z-score (1.960 used for 95% confidence interval)
- σ = population standard deviation

This study's target sampling locations totaled approximately 10,000 employees per site. A target sample size of 370 for each site was estimated to be sufficient for obtaining a 95% confidence interval (CI) with a 5% margin of error (MOE) based on recommendations by Krejcie and Morgan (1970).

4.3.1 Factor Analysis

Confirmatory factor analysis (CFA) tests for appropriate relationships between observed and latent variables in a model and is a first step toward later establishing causal relationships with Structural Equation Modeling (SEM; Schreiber et al., 2006; Ullman & Bentler, 2003). Several studies on sample size are needed specifically for using factor analysis in this type of research. The suggested numbers range from only ten per variable up to more than 300 (Anderson & Gerbing, 1988; Bentler & Chou, 1987; Boomsma & Hoogland, 2001; Gorsuch, 1983; Kline, 2015; Marsh et al., 1998; Muthén & Muthén, 2002; Schreiber et al., 2006; Westland, 2010). Table II summarizes each source and the number of suggested responses.

Based on the literature, it was determined that a sample size of 370 would exceed any suggested requirement for factor analysis.

Table II. Suggested Sample Size for Factor Analysis

Source	**Suggested Sample Size**
Bentler & Chou (1987)	10:1 response:factor ratio In this case, $N \geq 60$
Schreiber et al. (2006)	10:1 response:factor ratio In this case, $N \geq 60$
Westland (2010)	$N \geq 50r^2 – 450r + 1100$, where r = ratio of observed variables to latent variable In this case, r = 4 so N>100
Gorsuch (1983)	$N \geq 100$
Anderson & Gerbing (1988)	$N \geq 150$
Kline (2015)	$N \geq 200$
Marsh et al. (1998)	$N \geq 200$
Muthén & Muthén (2002)	$N \geq 265$
Boomsma & Hoogland (2001)	$N \geq 300$

4.4 Measures

A Likert survey instrument was chosen for sampling due to its ability to gather multiple participant opinions anonymously for multiple survey statements. Using a Likert scale also provides a standard set of participant responses to ease large sample data analysis.

4.4.1 Survey Research

Several data collection methods exist, such as direct measurement, observation, and surveys. If the goal is to obtain individuals' opinions, neither observation nor direct measurement is applicable. Surveying is one possible method of collecting opinions that is non-invasive and can be anonymous.

Surveys are used in empirical research to administer a set of questions or statements to participants to gain their opinions and information related to the research question (Check & Schutt, 2011). Quantitative items can be used to obtain numerical and precise data, qualitative items can be used to obtain categorical data, or the researcher may use a combination of both types (Cohen et al., 2002).

4.4.1.1 Sampling Strategy

When developing a survey, one must first choose a sampling strategy that can be used to collect data on the target population (Henry, 2009; Kalton, 2020; Kish, 1965). The strategy must consider specific factors to be studied, sample size, population characteristics in relation to the sample, and participant accessibility (Cohen et al., 2002). The primary two types of sampling are probability sampling and non-probability sampling. While researchers typically choose probability sampling whenever possible to increase the chances of a representative sample (Visser et al., 2000), it is not always feasible due to participant availability or willingness, anonymity requirements, and the logistics of administering the survey. However, a voluntary sample can be compared to population demographics to assess whether a representative sample was collected.

4.4.1.2 Survey Design

After selecting a sampling strategy, researchers must decide on a survey design that will provide the most reliable and valid data (Visser et al., 2000). Several considerations must be made that could determine the success or failure of the survey, including open-ended versus closed-ended items, use of rating versus ranking scales, type of rating scale, the inclusion of response options in addition to the rating scale, statement wording, and item order. Additionally, if modifying an existing survey, researchers must choose which items to use and whether to modify the wording of the items. However, it is important to remember that there is no scientific way to develop a survey, and it is up to the researcher to decide which methods to follow (Malhotra, 2006).

Open-ended and closed-ended statements each have advantages. Open-ended statements allow participants to answer precisely how they want without any limitations on wording or answer choices. Responding to open-ended questions may be advantageous to participants, but researchers must categorize the responses with clear and specific criteria. This can lead to an extremely high data processing time and introduce errors to the data if not transcribed and coded correctly (Cohen et al., 2002; Malhotra, 2006; Visser et al., 2000). Closed-ended statements reduce processing time as they are already pre-sorted into specific response categories. Participants may also prefer this type of survey item because it is faster to answer, but incomprehensive answer choices can lead to confusion and even frustration (Boynton & Greenhalgh, 2004; Houtkoop-Steenstra & Houtkoop-Steenstra, 2000). Converse (1987) reports that data collected by closed- versus open-ended items are of equal quality, rendering the additional resources needed to administer and analyze open-ended items unnecessary. This has increased the use of closed-ended items in survey research (Smith, 1987).

Another consideration is whether researchers plan to use a response scale and whether it will be a rating or ranking scale. Rating scales involve an incremental selection of response choices in one category, whereas ranking scales require participants to order response choices comparatively to one another. Ranking scales are helpful when researchers want participants to prioritize responses but require more time to answer and can lead to participant bias when comparing one response to another (Alwin & Krosnick, 1985; Visser et al., 2000). Rating scales – such as the Likert scale (Likert, 1932) – measure a single item and do not require comparing one item to the next (Oppenheim, 1992). When collecting participants' opinions on a given topic, the Likert scale is one of the most advantageous as it allows for several different responses indicating a level of disagreement or agreement with a statement or question (Likert, 1932;

Norman, 2010). Additionally, using words to label scales (i.e., agree, disagree) has been shown to help clarify the scale's meaning and increase reliability and validity (Krosnick & Berent, 1993; Peters & McCormick, 1966).

Malhotra (2006) recommends the following considerations for Likert scale use:

- The number of response choices on the scale
- The ratio of favorable to unfavorable survey items
- Odd or even number of response choices
- Forced versus non-forced choice

In choosing the number of response options on the rating scale, researchers should have at least two, with increasing statistical advantage up to seven (Krosnick, 2018). Malhotra (2006) suggests that the number of favorable and unfavorable items should be equal, as this leads to more objective data. However, oppositely worded statements can lead to confusion and response error (Benson & Hocevar, 1985). Additionally, if there are both positive and negative statements, researchers must ensure that reverse scoring is done on one type of statement or the other to ensure consistent analysis. In choosing an odd versus even number of response choices, researchers should use an odd number unless it can be reasonably assumed that no respondent will have a neutral or indifferent opinion.

If using a rating scale, researchers must decide whether to add any response options in addition to the scale. If participants have no opinion or do not wish to disclose an opinion, the survey must allow for this option so that data are not skewed toward the neutral standpoint (Malhotra, 2006). An alternate choice not on the scale may help reduce frustration related to non-comprehensive answer choices as it allows an opt-out of choosing an item on the scale. One of the add-on response options is “I don’t know.” This can allow participants to select if they do not understand the item or response options (Cohen et al., 2002; Visser et al., 2000; Feick, 1989). However, if participants are not motivated or able to answer an item (Krosnick, 1991) or if they wish not to put effort into answering (Oppenheim, 1992), they could answer "I don't know," affecting the quality of the data. Adding "I don't know" as an option is debated in the literature and may be situational depending on the particular study goals and parameters (Krosnick et al., 2002; McClendon & Alwin, 1993). An alternative is to allow participants to skip the item and communicate that this is an option.

It is important to control response variation by having participants answer the same statements (Fowler & Mangione, 1990; Visser et al., 2000). Poorly worded items on a survey may lead to participant frustration, voluntary withdrawal, and nonresponse error (Malhotra, 2006). Krosnick (2018) provided the following list of considerations on survey item wording:

- Use simple, familiar words (avoid technical terms, jargon, and slang).
- Use simple syntax.
- Avoid words with ambiguous meanings, i.e., aim for wording that all respondents will interpret in the same way.
- Strive for specific wording and concrete (as opposed to general and abstract).
- Make response options exhaustive and mutually exclusive.
- Avoid leading or loaded questions that push respondents toward an answer.
- Ask about one thing at a time (avoid double-barreled questions).
- Avoid questions with single or double negations.

While there is support in the literature for choosing a certain way to order items on a survey (Krosnick, 2018; Malhotra, 2006), there are some disadvantages to presenting them in a fixed order. These include order effects and straight-line responding, which introduce bias to survey responses (Barge & Gehlbach, 2012; Krosnick, 1991). While random question ordering applies to the Likert portion of the survey, it is agreed that all demographic information should be collected at the beginning (Malhotra, 2006).

4.4.1.3 Survey Delivery

Once the sampling strategy and survey format are finalized, data can be collected. Researchers may choose to deliver their survey via traditional paper survey in-person or via mail, an electronic survey delivered via phone, email, or an online survey forum, or a combination of the two (Bradburn et al., 2004; Cohen et al., 2002; Dillman et al., 2014; Fowler, 2013). The data collection method a researcher selects is situational and may vary based on several factors (Visser et al., 2000). An advantage of in-person surveying is that the researcher is present to clarify and answer any participant questions. However, a disadvantage is that participants may feel rushed to complete the survey if the researcher is present (Cohen et al., 2002). Additionally, the anonymity of participants cannot always be ensured for in-person surveying.

Ponto (2015) provided a comprehensive table of possible errors, sources of the errors, and ways to help reduce the errors (Table III). Unfortunately, even the best-planned surveys cannot eliminate all bias (Krosnick, 1999; Visser et al., 2000). Researchers must ensure all reasonable measures are taken to avoid error and acknowledge any limitations to consider in interpreting the results.

Table III. Sources of Error in Survey Research and Strategies to Reduce Error (Ponto, 2015)

Type of error	**Source of error**	**Strategies to reduce error**
Coverage error	Unknown or zero chance of individuals in the population being included in the sample	Multimode design
Sampling error	Individuals included in the sample do not represent the characteristics of the population	Clearly identified population of interest; diverse participant recruitment strategies; large, random sample
Measurement error	Questions/instruments do not accurately reflect the topic of interest; questionnaires/interviews do not evoke truthful answers	Valid, reliable instruments; pretest questions; user-friendly graphics, visual characteristics
Nonresponse error	Lack of response from all individuals in sample	User-friendly survey design; follow-up procedures for non-responders
Note: Information from Dillman et al. (2014), Singleton & Straits (2009), Check & Schutt (2012).		

4.4.1.4 Accuracy, Reliability, and Validity of Survey Instruments

Additional important considerations in survey research are the survey's accuracy, reliability, and validity. A well-developed survey with clear items and response options should lead to more accurate data (Ponto, 2015). Measuring the internal consistency of survey items can establish reliability, meaning that a survey has homogeneity across the individual items (Sekaran & Bougie, 2019). The standard internal consistency test is Cronbach's coefficient alpha (Cronbach, 1951).

Validity is a more complex construct consisting of three types: construct validity, content validity, and criterion-related validity. Construct validity determines the level to which the survey instrument fully represents all target concepts of the study (Sekaran & Bougie, 2019). This is further decomposed into convergent and discriminant validity (Campbell & Fiske, 1959). Convergent validity describes the level to which two measures of the same concept supposed to be correlated are correlated, and discriminant validity describes the level to which measures that are supposed to be uncorrelated are, in fact, uncorrelated (Sekaran & Bougie, 2019). Factor analysis and structural equation modeling are useful in establishing types of validity (Garver & Mentzer, 1999; Henseler et al., 2015; Kline, 2015; Sekaran & Bougie, 2019).

Content validity is qualitative and describes the level to which the survey instrument measures the intended concepts of the study (Bollen, 1989b; Sekaran & Bougie, 2019). In other words, content validity measures how comprehensively the survey items describe the factors being studied. This can be established through a subject matter expert panel judgment (Drost, 2011). Face validity is a basic version of content validity that relies on the subjective agreement that a survey instrument measures what it is intended to measure (Cohen et al., 2002; Drost, 2011; Sekaran & Bougie, 2019).

Criterion-related validity describes the level at which item responses correlate with a concrete external criterion (Cohen et al., 2002; Drost, 2011). This can be measured via concurrent validity or predictive validity (Sekaran & Bougie, 2019), where concurrent validity refers to a concrete criterion currently in existence, and predictive validity refers to a concrete criterion occurring in the future (Drost, 2011). Concurrent and predictive validity are established via real-world observation compared with survey results (Drost, 2011). Criterion-related validity does not apply to pre-implementation studies, as there are no real-world observations to measure.

4.4.2 Pilot Phase: Survey Item and Scale Selection

The survey instrument was developed by integrating parts of the UTAUT and ORIC instruments into a single survey along with expert panel discussion and consensus on additional items beyond these two models. UTAUT is a validated synthesis of a variety of existing technology acceptance models, so it was used as the basis of the individual acceptance portion of the survey instrument. Venkatesh et al. (2000) found that self-efficacy, anxiety, and attitude are mediated by PEOU, and, therefore, effort expectancy. Effort expectancy is a primary construct in the final UTAUT instrument, so statements pertaining to self-efficacy, anxiety, and attitude were not included in the instrument. ORIC is an organizational technology acceptance model emphasizing the employee’s opinions of their organization, which was deemed potentially valuable in a technology acceptance model intended for the manufacturing environment. Both factors tested in ORIC, change commitment and change efficacy, were reported to be useful in gauging employee acceptance of technology. The expert panel reviewed the ORIC survey instrument and consolidated the statements deemed most applicable to a pre-implementation manufacturing context into three items. The proposed survey instrument included the three statements as one combined organizational readiness (OR) factor.

The resulting model includes the four main independent variables measured by UTAUT – PE, EE, SI, and FC- and the OR independent variable based on the ORIC model. BI was measured as a dependent variable. Definitions for each construct can be found in the introduction to UTAUT in Section 2.1.1.2. The resulting survey instrument consists of sixteen items in six categories corresponding to the six constructs being tested. Table IV shows all survey items by category.

Table IV. Breakdown of Pilot Survey Items

Construct	**Number of Items**
Performance Expectancy	3
Effort Expectancy	3
Social Influence	2
Facilitating Conditions	3
Organizational Readiness	3
Behavioral Intention	2
Total	**16**

All items were restructured to address the pre-technology implementation context rather than a post-implementation or mixed-tense structure currently found in the UTAUT and ORIC instruments. This was done by wording statements in the future rather than present or past tense. In some cases, statements were changed to a hypothetical context rather than a guaranteed-implementation context to account for initiatives where a decision on implementation has not been made. A summary of pilot phase wording changes can be found in Appendix A, and the pilot phase survey instrument can be found in Appendix B.

Due to the variety of available I4.0 technologies and their potential applications, it is important for participants to answer survey statements with the same technology in mind. One individual's level of acceptance for 3D printing, for example, may be different from that same individual's level of acceptance for autonomous robots. For this reason, the scope of this study was narrowed to one specific AR technology with direct applicability to manufacturing. AR is relevant to manufacturing because it combines physical and virtual domain capabilities to allow for quicker, more informed decision-making (Erboz, 2017). For example, AR has the capability for applications such as establishing flexible parts picking sequences and displaying part installation instructions to employees on the production line.

Due to the conflicting literature on adding an "I don't know" option to survey items (Krosnick et al., 2002; McClendon & Alwin, 1993), the decision was made not to include it in the current survey instrument. Specifically, this was decided due to the possibility of participants trying to complete the survey more quickly or not putting effort into answering if given an "I don't know" option. The chances of participant confusion and frustration are reduced by expert panel feedback to ensure all statements are clearly worded, and by participants' ability to skip any item.

After demographic information questions, a Likert scale was chosen for item responses related to the main factors being studied. A five-point scale was chosen for simplicity in responding, ranging from 1 (strongly disagree) to 5 (strongly agree).

The resulting survey instrument and model is the Technology Acceptance Model for the Manufacturing Environment (TAME). Three experts reviewed the survey with extensive experience in surveys and technology adoption. These experts provided feedback on wording, content, and the number of items for all survey sections. Once the agreement was reached on survey adequacy, a pilot was conducted to evaluate the construct validity of the TAME instrument.

4.4.3 Pilot Survey Development Summary

Survey development for TAME encompasses many existing technology acceptance models and includes constructs PE, EE, SI, FC, OR, and BI. Venkatesh et al. (2003) proposed and validated a model based on eight previous models, the UTAUT, which includes the PE, EE, SI, FC, and BI constructs used in TAME. Items for OR came from ORIC, a technology acceptance model focused on organizational readiness (Shea et al., 2014). Survey items were changed from a post-implementation to a pre-implementation context, and minor wording changes were made based on feedback from the expert panel. A pilot phase of the study was then employed to test the survey instrument.

4.5 Pilot Study Phase

Before a full research study commences, it is recommended to conduct a pilot to test for feasibility (Malhotra, 2006; Van Teijlingen & Hundley, 2001). Pilot studies typically have a smaller sample size than a full study, and results are not robust enough to draw meaningful conclusions. However, they still provide useful information to a researcher when checking various elements of a survey instrument. It is important to determine pilot phase objectives before running the study (Thabane et al., 2010). The objectives of the pilot phase were to test the internal consistency and face validity of the survey instrument, confirm the effectiveness of the delivery method, and identify statistical analysis methods for the full-scale phase.

4.5.1 Methods

The Auburn Institutional Review Board (IRB) approved the initial study, Protocol #21-528 EX 2111 (Appendix C). A link and QR code to the survey was sent via email to approximately twenty students working in a manufacturing environment and simultaneously enrolled in a Product Innovation course at Auburn University. The link and QR code were also sent to twenty-one individuals in the Advanced Manufacturing Research Group in the Industrial and Systems Engineering Department at Auburn University. These groups were chosen due to their similarities to the target population, as recommended in the literature (Diamantopoulos et al., 1994; Martin & Polivka, 1995). Participants were asked to take the survey from the perspective of an employee facing possible new technology implementation from his or her employer. Participants read a description of the technology being studied (e.g., "This technology typically includes a visual display and voice communication capabilities. Some uses are step-by-step job instructions, picking sequence, repair troubleshooting, and remote communication connectivity"). Participants then rated each survey item on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). To obtain feedback on the content validity of the survey, participants were asked to provide feedback regarding suggested wording changes, unclear descriptions, or other suggestions. Time taken to complete the survey was also recorded for each participant. Survey items were presented to participants one at a time and in random order to minimize order effects, avoid bias, and reduce the potential of straight-line responding.

4.5.2 Reliability and Content Validity Analysis

IBM SPSS Statistics Version 26 was used for reliability analysis calculations. Cronbach's alpha coefficient was used to measure internal consistency, or the extent to which the statements intended to measure the constructs (Streiner, 2003). While 0.7 and above is the generally accepted threshold for Cronbach's alpha scores (Nunnally, 1978), the score highly depends on the number of items for each construct (Pallant, 2016). For this reason, it is common to have low Cronbach's alpha scores for shorter survey instruments. If Cronbach's alpha score is below the acceptable threshold, Briggs and Cheek (1986) recommend checking each construct's average inter-item correlation, where a value between 0.2-0.4 is considered optimal. Harman's single-factor test was also used to rule out common method bias, which is when the survey itself influences participant responses. An ideal score is any value below 50%, meaning that no single construct accounts for the majority of covariance (Podsakoff et al., 2003). Content validity was tested via an expert panel and participant feedback regarding the survey instrument.

1.4.3 Pilot Study Phase Results

Twenty-six responses were received during the pilot phase. Demographic information was captured for each participant, summarized in Table V. Cronbach's alpha scores were calculated for each construct. Where the score did not meet the acceptable threshold of 0.7, inter-item correlation scores were calculated as a secondary measure of consistency. Internal reliability was confirmed for all items through either Cronbach's alpha or inter-item correlation, and results are reported in Table VI.

Table V. Pilot Demographic Information

Demographics (N=26)		Response
Gender	Male	54%
	Female	46%
Age	18-24 years	27%
	25-34 years	46%
	35-44 years	15%
	45-54 years	8%
	55+ years	4%
Time to Complete (Average)		2 minutes, 50 seconds
Withdrawal		0%

Table VI. Pilot Phase: Internal consistency results

Construct	Cronbach's Alpha Score	Average Inter-Item Correlation (where Cronbach's alpha <0.7)
Performance Expectancy	0.9	--
Effort Expectancy	0.7	--
Social Influence	0.7	--
Organizational Readiness	0.5	0.3
Facilitating Conditions	0.5	0.3
Behavioral Intention	0.9	--
Harman's Single-Factor Score		37%

Harman's single-factor score for the survey instrument was found to be 37%, which is considered acceptable. The ideal value is below 50% to ensure that no variable accounts for the majority of covariance.

4.5.3 Identification of Statistical Analysis Techniques for Full-Scale Phase

In addition to establishing survey instrument consistency, pilot studies can also be used to identify statistical analysis techniques for a full study. Confirmatory Factor Analysis (CFA), a type of Structural Equation Modeling (SEM), has been widely used to study relationships among constructs within a model and to confirm model validity (Anderson & Gerbing, 1988; Bollen, 2005; Brown, 2015; Kline, 2015).

Because Venkatesh et al. (2003) observed the effects of moderating variables in their proposal of UTAUT, it was decided to study whether any moderating variables exist when UTAUT (and later, TAME) is applied to a manufacturing sample in a pre-implementation context. The PROCESS version 3 macro developed for testing moderating effects in SPSS (Hayes, 2017) was used for this analysis.

To study interactions between sample groups, Agresti (2010) established that for non-parametric data like those typical of a Likert scale survey, the Mann-Whitney U test can be used in place of an independent t-test. The Mann-Whitney U test, along with the Kruskal-Wallis test in place of a one-way ANOVA, can determine whether relationships between two groups are significantly different (Bertram, 2007; Jamieson, 2004; McCrum-Gardner, 2008).

4.5.3.1 Confirmatory Factor Analysis (CFA)

Since Jöreskog (1969) introduced CFA, it has become the most often used method to confirm the construct validity of a model and accompanying instrument (Brown, 2015; Brown & Moore, 2012; Schreiber et al., 2006; Strauss & Smith, 2009). Construct validity includes convergent validity, or the extent to which two different constructs of the same measure are correlated where expected, and divergent validity, or the extent to which two constructs are not correlated where expected (Sekaran & Bougie, 2016; Trochim & Donnelly, 2006). CFA is an important step in establishing relationships between observed and latent variables in a hypothesized model and must be conducted prior to a causal analysis between latent factors via Structural Equation Modeling (SEM; Schreiber et al., 2006; Ullman & Bentler, 2003).

In a CFA, the researcher first creates a hypothesized model based on theoretical relationships between observed and latent variables (Schreiber et al., 2006). Observed variables can be directly measured via the instrument accompanying a model (for example, a survey). Latent variables are unobservable and therefore inferred from observed variables (Bollen, 2005; Kline, 2015; Schreiber et al., 2006). In creating a CFA model, a square or rectangle denotes an observed variable, and a circle denotes an unobserved or latent variable (Schreiber et al., 2006). One may use a curved arrow to denote a possible covariance with no known direction of effect and straight arrows to denote hypothesized direct effect relationships (Schreiber et al., 2006; Ullman & Bentler, 2012). The CFA then calculates hypothesized versus observed covariances between variables to confirm or reject the hypotheses depicted in the proposed model. Schreiber et al. (2006) provide an example of a general CFA model (Figure 6).

Sampling Adequacy

To determine whether a data set is appropriate for CFA, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) may be used to find the proportion of common variance among variables (Kaiser, 1974). Higher KMO values are preferred, and values between 0.8 and 1 are ideal, indicating a lower spread of correlations among variables than the sum of correlations (Cerny & Kaiser, 1977; Field, 2013).

Bartlett's test for Sphericity is used to test for adequate redundancy between variables to be indicated by a set of factors (Armstrong & Soelberg, 1968; Snedecor & Cochran, 1989). An ideal result indicates a level of significance < 0.05 (Snedecor & Cochran, 1989). IBM SPSS

Statistics Version 26 was used to perform KMO and Bartlett’s test for Sphericity to confirm viability of CFA.

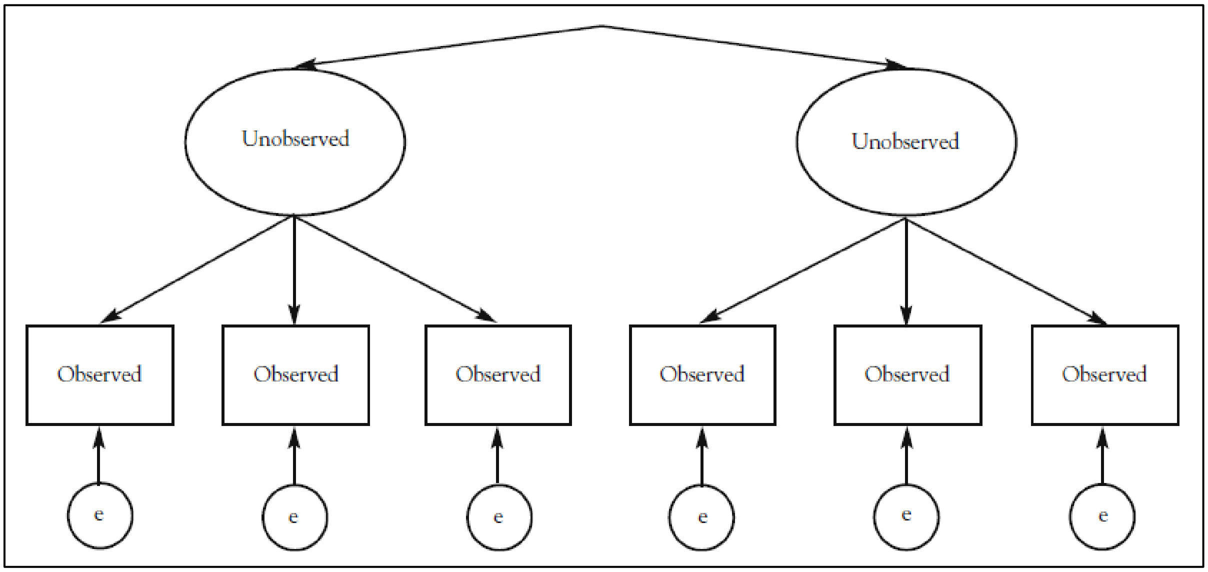

Figure 6. Generic example of a confirmatory factor analysis. e = error. (Schreiber et al., 2006)

Model Fit Indices

To validate a CFA or SEM model, one must determine its goodness-of-fit or whether the interactions of variables within the model perform per the researcher's hypotheses (Hu & Bentler, 1999). Various fit indices are available to researchers. The literature varies widely on which indices are most appropriate for which data set or even if specific fit indices are appropriate (Kenny, 2015). The most often-used measure of fitness is the chi-square goodness-of-fit statistic (Gierl & Mulvenon, 1995; Jöreskog, 1969; Maydeu-Olivares, 2017). However, for sample sizes greater than 200 (Kenny, 2015), or for models with a large number of observed variables (more than 17), the chi-square test does not adequately determine goodness-of-fit (Shi et al., 2019). This is due to an inflated Type I error rate is known as the model size effect (Herzog et al., 2007; Moshagen, 2012; Shi et al., 2015, 2017; Yuan et al., 2015). This can cause a paradoxical problem in research because increased model size can have many advantages, such as higher reliability (Lord & Novick, 1968; McDonald, 1999) as well as "more proper solutions and more accurate parameter estimates" (Marsh et al., 1998). Therefore, a chi-square test may show that a reliable and accurate model is not a good fit simply because of many observed variables. The chi-square test assumes no difference between the model and the true process it describes, which is rarely the case (Box, 1979; MacCallum, 2003). This may lead to the rejection of the null hypothesis when the model is, in fact, a reasonable fit (Shi et al., 2019). For these reasons, the chi-square test should be used cautiously, and researchers should exercise judgment in reporting it (West et al., 2012).

Due to emerging concerns with the chi-square test, fit indices were developed to better explain model fit for various data sets (Bentler & Bonett, 1980). It is now recommended to use measures based on the two types of model fit: absolute and incremental (Bollen, 1989a; Gerbing & Anderson, 1993; Hu & Bentler,1995; Marsh et al., 1988; Tanaka, 1993). Absolute fit measures to what degree the data patterns match the expected parameters of a given model (Hu & Bentler, 1999). The root mean square error of approximation (RMSEA) is the absolute fit index most frequently recommended and reported in the literature (Hancock et al., 2018; Kenny et al., 2015; McDonald & Ho, 2002; Savalei, 2012) and is regularly utilized in SEM software (Shi et al., 2019). The RMSEA is a "badness-of-fit" measure showing the discrepancy between a population covariance matrix and a model covariance matrix as they relate to degrees of freedom (Steiger, 1989, 1990; Steiger & Lind, 1980). Values fall between 0 and 1, and lower values are ideal as 0 indicates a best-fit model (Kenny, 2015). Acceptable RMSEA values are below 0.08 (Browne & Cudeck, 1993; MacCallum et al., 1996; Steiger, 1989). The RMSEA is appropriate for models with many directly observable variables, even decreasing with increased model size (Breivik & Olsson, 2001; Kenny & McCoach, 2003; Savalei, 2012).

Incremental fit indices measure a proportionate change in fit when an ideal model is compared with a baseline model (Bentler & Bonett, 1980). The comparative fit index (CFI) (Bentler, 1990) was the first of the incremental fit indices and has shown strong performance in power and robustness tests (Hu & Bentler, 1998). It is one of the most frequently used incremental fit statistics in SEM software (Shi et al., 2019). Values range from 0 to 1, with 1 indicating an ideal model fit and an acceptable cutoff value greater than 0.09 (Bentler, 1989; Bentler & Bonett, 1980).

CFI and RMSEA are functions of the chi-square test and, therefore, potentially susceptible to the same model and sample size biases (Moshagen, 2012; Shi et al., 2017). However, in a study on the impact of model and sample size on fit indices, CFI and RMSEA were found acceptable for use in models with more than ten directly observable variables and sample sizes over 200 (Shi et al., 2019).

Convergent Validity

In order to establish the convergent validity of the CFA models in this study, factor loading and composite reliability (CR) parameter estimations were done based on recommendations in the literature (Anderson & Gerbing, 1988; Hair, 2006; Raykov, 1997).

Factor loading measures the magnitude of a set of observed variables on a single latent variable. Research suggests factor loadings greater than 0.3 for samples larger than 350 (Hair, 2006) or greater than 0.6 for any sample size (Field, 2013; Guadagnoli & Velicer, 1988; MacCallum et al., 2001) are considered significant. SPSS Amos Version 28 was used to calculate factor loadings for each observed variable in relation to the latent variable it corresponds to in the CFA model.

Factor loadings allow for the calculation of CR, a measure of internal consistency suggested to complement Cronbach's coefficient alpha (Anderson & Gerbing, 1988; Hair, 2006; Raykov, 1997). The measure of CR indicates how consistently observed variables are in their measurement of a given latent variable (Hair, 2006). Scores above 0.6 are acceptable, and values above 0.8 are preferred (Hair, 2006; Nunnally & Bernstein, 1994). As Cronbach's coefficient alpha scores for two of the six constructs in the pilot study phase did not meet acceptable thresholds, it was decided to utilize this additional measure of internal consistency in the full-scale phase to confirm the model's reliability.

Discriminant Validity

Discriminant validity is paired with convergent validity to establish the overall construct validity of a model (Sekaran & Bougie, 2016; Trochim & Donnelly, 2006). To determine discriminant validity, the Heterotrait-Monotrait Ratio of Correlations (HTMT) has been suggested as an improvement to the traditionally used square root of Average Variance Extracted (Henseler et al., 2015; Ab Hamid et al., 2017). The HTMT takes heterotrait correlations, or average correlations of observed variables with latent variables they do not correspond to, and compares them to monotrait correlations, or average correlations of observed variables with their suggested corresponding latent variable. The resulting values should be no greater than 0.9 (Gold et al., 2001; Teo et al., 2008).

4.5.3.2 Structural Equation Modeling (SEM)

After CFA is conducted and construct validity confirmed, directional relationships between independent variables PE, EE, SI, FC, and the dependent variable BI can be explored via SEM. SEM is a broader method of CFA (Schreiber et al., 2006; Ullman & Bentler, 2012) used to show how the independent variables relate to dependent variables rather than one another

(Bollen, 2005; Brown, 2015; Kline, 2015). SEM models show the interaction between independent (e.g., exogenous) and dependent (e.g., endogenous) variables, either directly, indirectly, or through each other (Baron & Kenny, 1986; Schreiber et al., 2006). The same labeling pattern as the CFA model is used for SEM (Figure 7). SPSS Amos version 28 was used for the analysis of CFA and SEM.

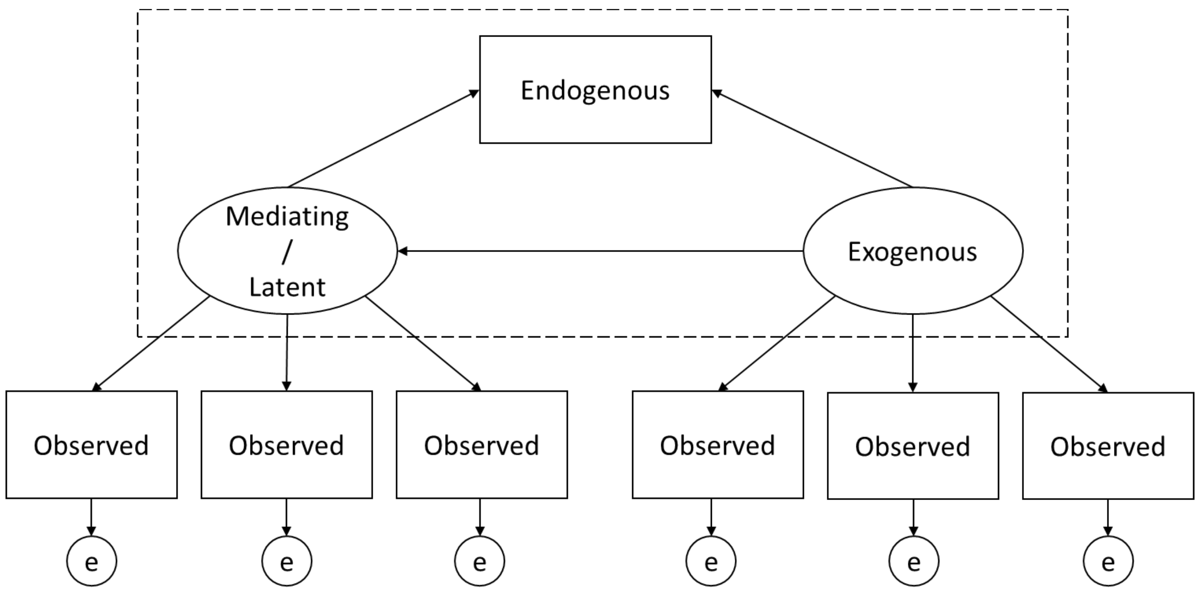

Figure 7. Generic example of a structural equation model. e = error.

There are several ways to conduct SEM in statistical modeling software. The most well-established method is Maximum Likelihood (ML), which assumes continuous variables with a parametric or normal distribution (Bollen, 2005; Brown, 2015; Kline, 2015). Historically, there has been heavy debate on whether parametric tests may be used for non-parametric ordinal data sets (Gardner, 1975; Feinstein, 1977; Knapp, 1990; Kuzon et al., 1996), and further debate on Likert scale data specifically (Jamieson, 2004; Norman, 2010). Some researchers have found that other parameter estimation methods, such as robust weighted least squares, are more appropriate than ML for ordinal data (DiStefano & Morgan, 2014; Mindrila, 2010). However, recent research on real (i.e., not simulated) Likert scale data has suggested that parametric analysis methods are appropriate for Likert scales (Mircioiu & Atkinson, 2017; Mondiana et al., 2018). Due to evidence that there is no difference in SEM analysis results when Likert scale data is treated as an interval (i.e., continuous) versus ordinal (Mondiana et al., 2018), the traditionally accepted ML method was used in this study.

4.5.3.3 Moderating Variables

In addition to analysis between independent and dependent variables directly, the PROCESS macro was developed to detect any outside variables that may affect the relationships between independent and dependent variables (Hayes, 2017). Moderating variables affect the power or directionality of a link between an independent and dependent variable (Edwards & Lambert, 2007; Hair, 2006; James & Brett, 1984). Moderating variables are not a part of the structural relationship between an independent and dependent variable; they only affect the relative strength or weakness. Hayes & Rockwood (2016) provide a visual example of a moderating variable, where the interaction between independent variable X and dependent variable Y is moderated by some variable W (Figure 8). Venkatesh et al. (2003) found that experience, age, and gender moderate various independent variables with respect to BI in UTAUT. Therefore, this study aimed to discover whether the same moderating relationships exist in a manufacturing environment. Cucos (2022) suggests the PROCESS macro in SPSS for calculating the effects of moderating variables.

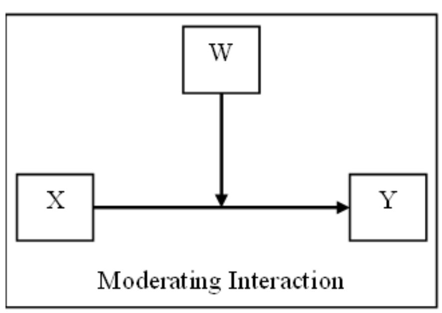

Figure 8. Moderating variable effect

4.5.3.4 Exploratory Analysis

In addition to CFA and SEM, descriptive statistics and comparison tests were conducted as an exploratory analysis of varying demographics in the data.

Box plots were created for each sub-group to compare various sub-samples of the data visually. Data were analyzed by region, facility location, department, job role within the organization, age, gender, and level of experience in manufacturing. Comparing data distribution and discovering outliers provides valuable insight for the organization that is further explored in the Discussion chapter.

The demographic sub-groups were also compared for statistical differences via the Kruskal-Wallis test for multi-group analysis and the Mann-Whitney U test for two independent groups, which are suggested as non-parametric alternatives to the traditionally used two-sample t-test and ANOVA for normally distributed data (Bertram, 2007; Jamieson, 2004; McCrum-Gardner, 2008). Kolmogorov-Smirnova and Shapiro-Wilk tests may be used to determine the normality distribution of data, where a significant value ($p < 0.05$) indicates a non-normal distribution. In this study, these tests were used to confirm the expected non-normality of the data distribution given the Likert scale survey instrument.

As a secondary measure of the differences between groups, effect size was calculated for any groups with statistically significant differences to establish the magnitude and practical interpretation of the differences, per recommendations from the literature (Coe, 2002; Wilkinson et al., 1999). For non-normal data, Rosenthal (1994) recommends calculating the effect size r by dividing the Z-score by the square root of the sample (N). A score less than 0.3 indicates a small effect size, 0.3 – 0.5 indicates a medium effect size, and 0.5 or above indicates a large effect size (Bhandari, 2022).

Lastly, a few select multi-factor analyses were run to explore the relationships between some of the sub-groups where a multi-factor interaction was thought to be possible. A multi-factor ANOVA (two or more interactions) was chosen due to the fact that the Kruskal-Wallis test only replaces a one-way ANOVA (Bertram, 2007; Jamieson, 2004; McCrum-Gardner, 2008). No other acceptable non-parametric equivalent to ANOVA could be found in the literature, and the ANOVA test is reported to be fairly robust to a non-normal distribution (Glass et al., 1972; Harwell et al., 1992; Lix et al., 1996).

4.5.3.5 Statistical Methods Summary

Statistical tests were chosen from recommendations in the literature based on the need to validate an existing model in a new context and initially validate a proposed model to compare the two. Additional tests were selected that allowed for additional exploration of differences between sub-samples of particular interest in a manufacturing context. Table VII summarizes the statistical methods used and at what phase each was deployed.

4.5.4 Pilot Study Phase Summary

The objectives of the pilot phase were as follows:

1. Test dissemination process of the survey instrument.
2. Establish internal consistency and face validity of survey instrument.
3. Identify and, where possible, preliminarily test statistical analysis methods for the full-scale phase.

The first objective was achieved via distribution to a curated sample of individuals with an interest or experience in manufacturing technology. No concerns with the delivery method, formatting, or access were identified. The second objective was achieved via reliability analysis and feedback from study participants and an expert panel. Reliability analysis was overall acceptable but indicated possible improvement with additional survey items and a larger sample size. Participant and expert panel feedback led to additional measurement items and changes to the introduction and technology description for the full-scale phase, which is discussed in depth in Section 4.6.1. The third objective was achieved by researching various available statistical analysis techniques and selecting appropriate tests to establish model validity and identify differences between groups.

Table VII. Statistical Analysis Technique Summary

Objectives	**Items**			**Methods**	**Test**
Validation of the assessment instrument	Reliability	Internal consistency		Reliability analysis	Cronbach's Coefficient Alpha Harman's single factor test
	Validity	Content validity	Face validity	Expert review Pilot study feedback	Consensus
		Construct validity	Convergent validity	Confirmatory Factor Analysis (CFA)	Factor loading Composite reliability (CR)
			Discriminant validity		The heterotrait-monotrait ratio of correlations (HTMT)
Confirmation of directional relationships	--	--	--	Structural Equation Modeling (SEM)	Effect of latent constructs on dependent variable
Investigation of moderating effects Gender, Age, Experience	Moderating effect	--	--	PROCESS macro	Moderating effect
Comparison between groups	--	--	--	Non-Parametric Testing	Kruskal-Wallis Mann-Whitney U test

4.6 Full-Scale Study Phase

Based on pilot results, the survey instrument appears to capture several independent constructs in pre-implementation technology acceptance in manufacturing. After preliminary confirmation of acceptable internal consistency and face validity, a more robust set of data was obtained to extend the model to the target population. Several techniques were identified to establish the validity of the pre-implementation UTAUT and TAME models, determine whether any moderators exist, and explore differences across sub-samples of the population. These include reliability analysis of the survey instrument, validity testing, and additional exploratory analysis methods.

The aims of the full-scale phase were as follows:

1. Establish content and construct validity of UTAUT in a pre-implementation manufacturing context.
2. Determine whether adding an organizational readiness component (resulting survey instrument: TAME) strengthens the UTAUT model for a manufacturing context.
3. Investigate significant differences of sub-groups via exploratory analysis.
    - Determine whether moderating variables impact model constructs.
    - Determine differences in technology acceptance between sub-samples of the target population.

4.6.1 Modifications to Survey Instrument

The intent of removing or consolidating statements from UTAUT and ORIC was to shorten the survey instrument for a front-line manufacturing worker who may have limited time to take a survey. However, this may have inadvertently lowered the internal consistency of the instrument. Due to two low Cronbach’s alpha scores, it was decided to add one or more items to each construct and increase the sample size to improve the statistical power of the instrument, totaling four items per construct. The original UTAUT survey by Venkatesh et al. (2003) has four items per construct for PE, EE, FC, and SI, but some items were initially removed to reduce the time needed to complete the survey. For the full-scale study phase, all statements removed from the pilot phase were added back to the TAME survey instrument to increase statistical power. Participants completed the pilot survey in less than three minutes, so it was determined that moderately increasing survey length was not a concern. As UTAUT has only three statements in the behavioral intention section, an expert panel discussion helped determine one additional statement for this section. The expert panel also reviewed the ORIC survey instrument and utilized the intent of the statements to create one additional statement for the organizational readiness factor. This resulted in a 24-item survey instrument, summarized in Table VIII. The full instrument can be found in Appendix D.

Table VIII. Breakdown of Full Survey Items

Construct	**Number of Items**
Performance Expectancy	4
Effort Expectancy	4
Social Influence	4
Facilitating Conditions	4
Organizational Readiness	4
Behavioral Intention	4
Total	**24**

Although the five-point Likert scale was simpler for respondents, it was decided to increase the Likert scale from a five-point scale to a seven-point scale to accommodate reports in the literature of increased statistical power with seven items (Krosnick, 2018).

As a result of participant feedback in the pilot phase, the decision was made to alter the technology description and include a video for greater clarity. The referenced technology (Google Glass) was changed to the generic term AR as a more versatile construct. A short, three-minute video of potential applications of AR to manufacturing was added to the survey instrument to help familiarize participants without providing too much detail on one specific technology or application. The Auburn IRB approved all modifications (Appendix E).

4.6.2 Methods

The sample population is manufacturing employees over 18, the youngest age for human subject research permitted by the IRB, who may be involved in I4.0 technology implementation in the future at their place of employment. As such, a partnership between Auburn University and a large automotive manufacturer with locations in both the Southeastern United States and Mexico was created on the agreement that exploration of employee technology acceptance would be mutually beneficial to both the manufacturer and the University. The primary researcher, both an employee at the automotive manufacturer and a doctoral candidate at Auburn University, coordinated agreement from the manufacturer’s Human Resources and Legal teams. Additionally, a participation agreement was obtained from the Vice Presidents of Manufacturing and Engineering at all manufacturing locations to be studied. Non-disclosure agreements were signed by necessary parties from Auburn University and the manufacturer to protect the manufacturer's identity in any publications.

The researcher worked with the manufacturer’s Communications team to disseminate the survey electronically via the online survey distribution tool SurveyMonkey. A link and QR code were provided to a survey embedded in a company-wide app for employee communications and engagement. The survey link was included in the weekly company newsletter at all sites for approximately one month. One final reminder was sent out approximately six weeks after the survey was opened. There were no exclusions based on race, gender, age, or other demographics.

After opening the survey, employees were presented with an informational letter about the study's purpose, what to expect, and informing them of the voluntary nature of their participation (Appendix F). Employees wishing to proceed navigated to the next page, where the survey began. Participants read a short description of AR and watched a video of applications of the technology. Participants then rated each survey item on a seven-point Likert scale, ranging from one (strongly disagree) to seven (strongly agree). As in the pilot study phase, statements were presented to participants one at a time and in random order to minimize bias.

4.6.2.1 Translation of Survey Instrument

A Spanish version of the survey was disseminated at Mexican sites to accommodate non-native English speakers. A bilingual Spanish- and English-speaking manager responsible for technology innovations at the manufacturer being studied performed an initial translation of the survey instrument and accompanying materials from English to Spanish. He then sent the translations to a group of individuals at the Mexican facility to be studied and requested any feedback or changes. Once all agreed that the Spanish survey conveyed same intent as the English survey, the Spanish survey was sent back to the researcher, who worked with the Mexican Communications team to disseminate the survey. The video from the English version of the survey could not be translated into Spanish, so accompanying photos of similar AR applications with Spanish descriptions were included in the Spanish survey instrument. The researcher worked with the same bilingual manager to translate survey response items to English for analysis. The resulting Spanish version of TAME can be found in Appendix G. Translation of the English survey to Spanish was approved by the Auburn IRB (Appendix H).

Chapter 5: Analysis and Results

5.1 Full-Scale Phase: Analysis and Results

Eight hundred twenty-three responses were received for the full-scale phase. Four hundred fifty-eight of these were responses to the full TAME survey instrument, and three hundred sixty-five were responses to statements derived from the UTAUT instrument only (no OR component) due to an error in transcribing the English-only survey into SurveyMonkey. Demographic information is summarized in Table IX and Table X. No identifiable information was collected for any survey respondent, and all individual responses were kept confidential. Average time to complete the survey was 7m:20s with a standard deviation of 2m:46s.

Demographic information that could potentially reduce perceived anonymity of the survey, such as gender and age, was collected in a categorical format per recommendations from the literature. Giles and Feild (1978) report that response bias can occur if participants feel their anonymity may be compromised by the format of demographic questions. It is therefore recommended to provide categorical responses to demographic questions asking for sensitive information such as age in order to maintain perceived anonymity and reduce the risk of response bias and unanswered questions (Wilson & Rosen, 1975). Before beginning the survey, participants were informed that their participation was completely voluntary and that they could decline to answer any survey item or exit the survey at any time without penalty.

Table IX. Demographic Information for the Full-Scale Phase

Demographic Information (Questions left blank are not included in counts)		**Sample size (n)**
Total (n)		823
Region	United States	365
	Mexico	458
Location	US 1	115
	US 2	107
	US 3	143
	M 1	271
	M 2	88
	M 3	73
	M 4	21
Department	Final Assembly	93
	Body Shop	68
	Engineering	218
	Paint	48
	Logistics	81
	Quality	82
	Maintenance	126
	Stamping	31
Role	Engineer	218
	Front Line	248
	Manager	333
Gender	Male	730
	Female	88
	Non-Binary	4
Age (years)	18-24	32
	25-34	247
	35-44	237
	45-54	219
	55+	87
Manufacturing Experience (years) Mean (years): 16.2 Range (years): <1 – 50 Standard Deviation: 10.3	<1	6
	1-3	41
	3-5	53
	5-10	164
	10-15	95
	15-20	125
	20+	243

Table X. Detailed Demographic Information by Department

Department (Blanks not included)	**Gender**			**Age (years)**					
	Male	Female	Non-Binary	18-24	25-34	35-44	45-54	55-64	65+
Final Assembly (n)	76	16	1	4	23	26	29	10	1
Body Shop (n)	60	8	--	--	19	19	27	2	1
Engineering (n)	194	22	1	8	74	59	50	24	3
Paint (n)	38	10	--	3	9	17	13	6	--
Logistics (n)	69	11	1	6	27	27	16	5	--
Quality (n)	75	7	--	1	25	26	19	11	--
Maintenance (n)	123	3	--	5	39	29	34	18	1
Stamping (n)	30	1	--	--	8	14	8	1	--

5.1.1 General Analysis Process

Each statistical validation test was conducted twice in the full-scale phase analysis. First, testing was done on data collected on UTAUT-only constructs to establish model usability in a pre-implementation manufacturing context. Then, the same tests were conducted on TAME constructs to compare whether one survey instrument and model were more appropriate for the target population. IBM SPSS Statistics Version 26 was used to calculate reliability scores, moderating effects, and non-parametric testing to compare groups. IBM Amos Version 28 was used for CFA and SEM modeling. Microsoft Excel was used for CR and HTMT calculations.

After reliability was established via Cronbach's coefficient alpha and Harman's single factor tests, construct validity was determined. KMO and Bartlett's Test of Sphericity scores were obtained to establish sampling adequacy, and then a CFA model was built. Chi-square tests were determined to be inappropriate for use in these models due to the large sample size ($N > 200$) and a large number of direct observations (i.e., survey items = 20 for UTAUT and 24 for TAME) likely to result in a Type I error (see Herzog et al., 2007; Kenny, 2015; Moshagen, 2012; Shi et al., 2015, 2017; Yuan et al., 2015). Instead, RMSEA and CFI were calculated and reported as fit indices. After confirming the overall model fit, convergent validity was tested. Factor analysis measured individual survey item loading on each latent construct. CR was conducted with factor scores to test internal consistency further and complement Cronbach's alpha scores. Discriminant validity was tested with the HTMT method.

After the validity of the survey instrument was established, a full model with all independent and dependent variables was created and tested for viability via SEM. The same set of tests for validity and reliability were conducted for the SEM model as the CFA model.

Finally, an investigation was done on the possible effects of the moderating variables age, gender, and experience in manufacturing on each significant latent factor. Although not tested in the original UTAUT model (Venkatesh, 2003), experience in manufacturing was included as a possible moderator due to the idea that increasing knowledge of manufacturing processes and job familiarity may affect an individual's level of acceptance of new technology. Experience with the technology was considered a moderator in the original UTAUT model but was omitted. This study was conducted in a pre-implementation context, so prior experience with the surveyed technology was not considered a moderator. Voluntariness was also not considered a moderator since participants were not the final decision makers on whether a new technology would be implemented.

5.1.2 Analysis and Results: UTAUT

5.1.2.1 Reliability Analysis

Cronbach's coefficient alpha scores for UTAUT constructs in the full-scale phase (Table XI) were acceptable. Harman's single factor score was 47%, which was also acceptable. The results of these two tests suggested adequate internal reliability for the UTAUT model when applied in a pre-implementation context to a manufacturing population.

Table XI. Cronbach's Alpha Scores for UTAUT in the Full-Scale Phase

Construct	**Criteria: Acceptable**	**Score**	**Status**
Performance Expectancy	> 0.7	0.9	Acceptable
Effort Expectancy	> 0.7	0.9	Acceptable
Social Influence	> 0.7	0.8	Acceptable
Facilitating Conditions	> 0.7	0.7	Acceptable
Behavioral Intention	> 0.7	0.9	Acceptable

5.1.2.2 Confirmatory Factor Analysis

Although the UTAUT model has been previously validated, a CFA was conducted to re-validate the model in a pre-implementation context in the manufacturing domain and for direct comparison purposes with the TAME model. Initial sample testing was done to determine the appropriateness for CFA. The KMO test and Bartlett's Test of Sphericity were conducted, and satisfactory results are reported in Table XII below.

Table XII. Sampling Adequacy of the UTAUT Data in the Full-Scale Phase

Sampling Adequacy		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.951
Bartlett's Test of Sphericity	Sig.	0.000

After confirming sampling adequacy, a CFA model was created (Figure 9). Model fit was assessed with the RMSEA and CFI fit indices, which were determined to be satisfactory (Table XIII). A standardized factor loading was calculated for each survey instrument item in relation to the latent variable it represents. The results of factor loading are reported in Table XIV. All survey item loadings were determined to meet minimum thresholds, and most exceeded the ideal threshold.

Table XIII. Fit Indices for the UTAUT CFA Model

Fit Index	**Value**	**Acceptable Fit**	**Good Fit**	**Status**
RMSEA	0.067	< .08	< .06	Acceptable
CFI	0.953	> .90	> .95	Good

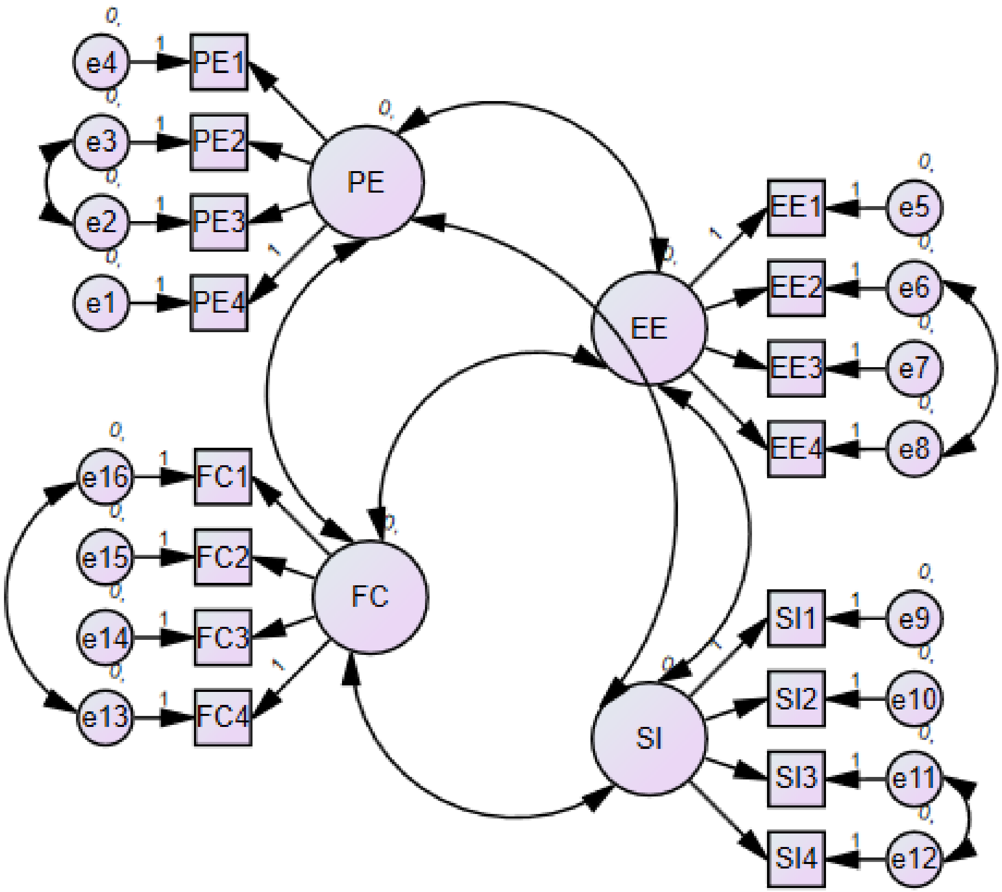

Figure 9. CFA model of UTAUT

Table XIV. Standardized Factor Loadings for the UTAUT CFA Model

	Factor Loading	**Criteria: Acceptable**	**Criteria: Good**	**Status**
Latent Variable: Performance Expectancy (PE)				
PE4	0.6	>0.3	>0.6	Good
PE3	0.8	>0.3	>0.6	Good
PE2	0.9	>0.3	>0.6	Good
PE1	0.9	>0.3	>0.6	Good
Latent Variable: Effort Expectancy (EE)				
EE1	0.8	>0.3	>0.6	Good
EE2	0.8	>0.3	>0.6	Good
EE3	0.8	>0.3	>0.6	Good
EE4	0.7	>0.3	>0.6	Good
Latent Variable: Social Influence (SI)				
SI1	0.8	>0.3	>0.6	Good
SI2	0.8	>0.3	>0.6	Good
SI3	0.7	>0.3	>0.6	Good
SI4	0.7	>0.3	>0.6	Good
Latent Variable: Facilitating Conditions (FC)				
FC4	0.5	>0.3	>0.6	Acceptable
FC3	0.7	>0.3	>0.6	Good
FC2	0.6	>0.3	>0.6	Acceptable
FC1	0.5	>0.3	>0.6	Acceptable

All CR values were determined to be acceptable (Table XV).

Table XV. CR Values for the UTAUT Model

Construct	**CR Value**	**Criteria: Acceptable**	**Criteria: Good**	**Status**
PE	0.879	> 0.6	> 0.8	Good
EE	0.852	> 0.6	> 0.8	Good
SI	0.823	> 0.6	> 0.8	Good
FC	0.659	> 0.6	> 0.8	Acceptable

Next, discriminant validity was determined via HTMT calculations. All HTMT values met the criteria of being no greater than 0.9, providing evidence that each construct is unique (Table XVI).

Table XVI. HTMT Correlations for UTAUT Model

	PE	EE	SI	FC
PE				
EE	0.833			
SI	0.812	0.729		
FC	0.880	0.894	0.841	

5.1.2.3 Structural Equation Modeling

After CFA was conducted with satisfactory results, SEM was used to create and analyze a model to determine the directional relationships of all independent and dependent variables (Figure 10). The same model fit indices as CFA (RMSEA and CFI) were calculated to establish the applicability of the full SEM model to the data set (Table XVII).

Table XVII. Fit Indices for the UTAUT SEM Model

Fit Index	**Value**	**Criteria: Acceptable**	**Status**
RMSEA	0.066	< .08	Acceptable
CFI	0.947	> .90	Acceptable

Factor loadings were calculated for each survey item and corresponding latent factor as well as each latent factor to the dependent variable. Factor loadings are reported in Table XVIII for the UTAUT model in SEM. All constructs were determined to have adequate convergent validity.

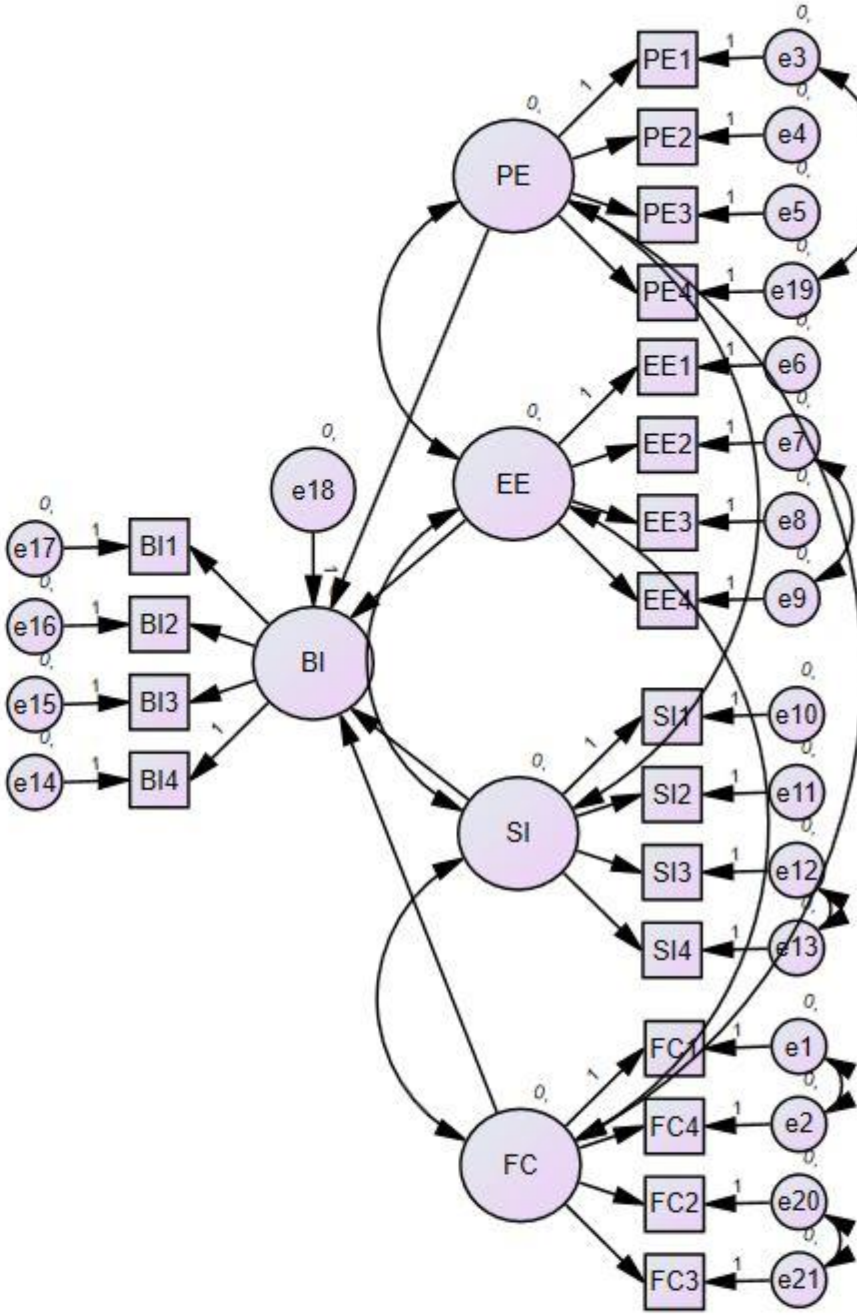

Figure 10. SEM model of UTAUT

Table XVIII. Standardized Factor Loadings for the UTAUT SEM Model

	Factor Loading	Criteria: Acceptable	Criteria: Good	Status
Independent Variable: Performance Expectancy (PE)				
PE4	0.6	>0.3	>0.6	Good
PE3	0.8	>0.3	>0.6	Good
PE2	0.9	>0.3	>0.6	Good
PE1	0.9	>0.3	>0.6	Good
Independent Variable: Effort Expectancy (EE)				
EE1	0.8	>0.3	>0.6	Good
EE2	0.8	>0.3	>0.6	Good
EE3	0.8	>0.3	>0.6	Good
EE4	0.7	>0.3	>0.6	Good
Independent Variable: Social Influence (SI)				
SI1	0.8	>0.3	>0.6	Good
SI2	0.8	>0.3	>0.6	Good
SI3	0.7	>0.3	>0.6	Good
SI4	0.7	>0.3	>0.6	Good
Independent Variable: Facilitating Conditions (FC)				
FC4	0.5	>0.3	>0.6	Acceptable
FC3	0.7	>0.3	>0.6	Good
FC2	0.6	>0.3	>0.6	Acceptable
FC1	0.5	>0.3	>0.6	Acceptable
Dependent Variable: Behavioral Intention (BI)				
BI1	0.9	>0.3	>0.6	Good
BI2	0.6	>0.3	>0.6	Good
BI3	0.9	>0.3	>0.6	Good
BI4	0.8	>0.3	>0.6	Good

The effect of each independent variable on BI was also measured via SEM and reported in Table XIX. PE and EE significantly affected BI, but SI and FC did not.

Table XIX. Relationships Between Independent Variables and BI

Construct	Estimate	p-value	Significant?
PE	0.526	< 0.001	Yes
EE	0.628	< 0.001	Yes
SI	0.116	0.113	No
FC	-0.318	0.074	No

The squared multiple correlation (R^2) for BI was 0.83, indicating that 83% of the variance in BI is accounted for by PE, EE, SI, and FC. The impact of PE and EE were both positive and significant, suggesting that increased PE and EE lead to an increase in BI in a pre-implementation manufacturing context. The impact of SI was positive but insignificant. The impact of FC was negative and insignificant. The insignificance of SI and FC indicates that neither construct can predict BI in a pre-implementation context.

5.1.2.4 Moderating Variables

Lastly, the possible effect of moderating variables on significant constructs was explored. Experience in manufacturing and the interaction of experience*gender was found to have a moderating effect on EE at a significance level of $p < 0.10$. The relationship between EE and BI was less salient for women than for men or non-binary individuals. Additionally, a higher level of experience weakens the positive effect of EE on BI. No moderating effects were discovered for PE. A summary of possible moderators and their effects is summarized in Table XX.

Table XX. Moderating Effects on UTAUT

DV: BI	**Exp**	**Age**	**Gender**	**Exp*Age**	**Exp*Gender**	**Age*Gender**
PE	0.2317	0.4358	0.4302	0.4923	0.1843	0.4749
EE	0.0563*	0.1783	0.2254	0.1343	0.0582*	0.1588

*$p < 0.1$, **$p < .05$, ***$p < .001$

The resulting UTAUT model most appropriate for manufacturing in a pre-implementation context is depicted in Figure 11. Although actual use in a pre-implementation context was not measured in either the pilot or full-scale phase, SI and FC were left in the model as possible antecedents of actual use. Venkatesh et al. (2003) reported a statistically significant relationship between FC and actual use. The MPCU (Thompson et al., 1991) and IDT (Moore & Benbasat, 1991) models suggest a significant relationship between SI and actual use. The reported significance of the relationships between FC, SI, and actual use in other models suggests the possibility of their significance to one another in the TAME model.

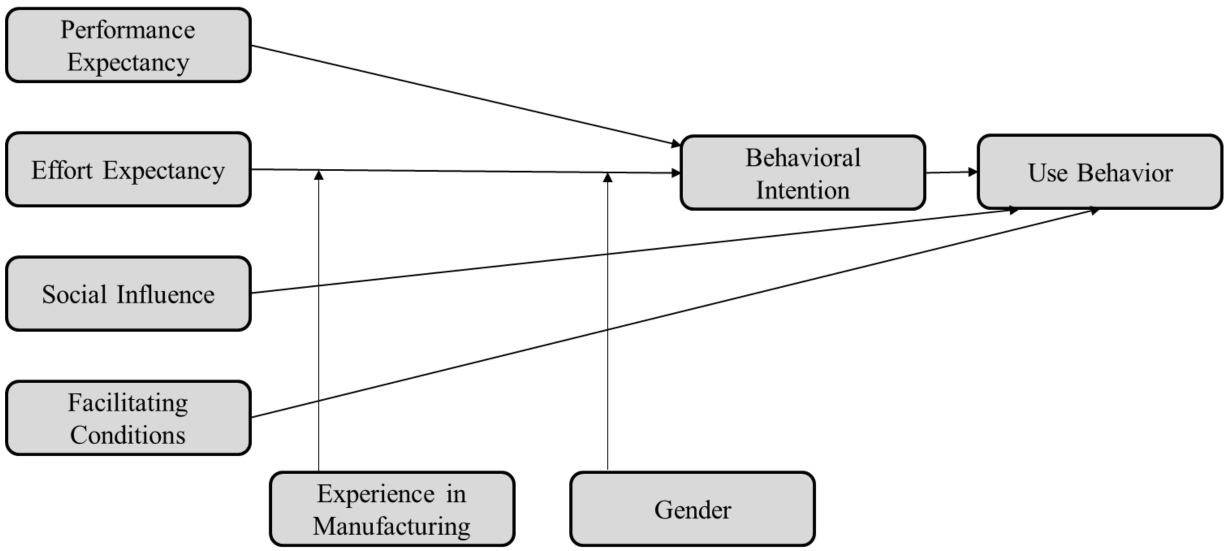

Figure 11. UTAUT in a pre-implementation context for manufacturing

5.1.3 Analysis and Results: TAME

5.1.3.1 Reliability Analysis

As in the UTAUT analysis, Cronbach's alpha (Table XXI) and Harman's single factor test (44%) were utilized to test the reliability and internal consistency of constructs deemed acceptable.

Table XXI. Cronbach's Alpha Scores for TAME

Cronbach's Coefficient Alpha			
Construct	**Criteria: Acceptable**	**Score**	**Status**
Performance Expectancy	> 0.7	0.8	Acceptable
Effort Expectancy	> 0.7	0.9	Acceptable
Social Influence	> 0.7	0.8	Acceptable
Organizational Readiness	> 0.7	0.8	Acceptable
Behavioral Intention	> 0.7	0.9	Acceptable

5.1.3.2 Confirmatory Factor Analysis

After confirming internal reliability, KMO and Bartlett's Test for Sphericity results suggested that the data met the criteria for a CFA analysis (Table XXII).

Table XXII. Sampling Adequacy for TAME Data

Sampling Adequacy		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.953
Bartlett's Test of Sphericity	Sig.	0.000

Initially, a CFA model was created with all independent constructs in the survey instrument: PE, EE, SI, FC, and OR. The initial iteration with all constructs returned scores of RMSEA = 0.09 and CFI = 0.883, indicating an unsatisfactory model fit. The lowest loading observed variable (FC1 → FC = 0.471) was dropped from the analysis to improve fit. The model fit indices improved slightly (RMSEA = 0.087, CFI = 0.9) but did not meet accepted values. Further attempts to drop the lowest loading observed variables resulted in an inability for SPSS Amos to calculate model fit. It was decided that since FC had the lowest loading observed variables in the initial iteration and was found insignificant to BI in the UTAUT analysis, it would be dropped from the CFA model for TAME. Fit index results of the TAME CFA model without FC were satisfactory and are summarized in Table XXIII.

Table XXIII. Fit Indices for the TAME CFA Model

Fit Index	**Criteria: Acceptable**	**Value**	**Status**
RMSEA	< 0.08	0.076	Acceptable
CFI	> 0.90	0.941	Acceptable

Once fit indices were deemed acceptable, analysis proceeded with the CFA model not containing FC (Figure 12). Factor analysis indicated that all observed variables load appropriately onto their respective latent constructs (Table XXIV).

Table XXIV. Standardized Factor Loadings for the TAME CFA Model

	Factor Loading	**Criteria: Acceptable**	**Criteria: Good**	**Status**
Latent Variable: Performance Expectancy (PE)				
PE4	0.6	>0.3	>0.6	Good
PE3	0.8	>0.3	>0.6	Good
PE2	0.8	>0.3	>0.6	Good
PE1	0.8	>0.3	>0.6	Good
Latent Variable: Effort Expectancy (EE)				
EE1	0.8	>0.3	>0.6	Good
EE2	0.8	>0.3	>0.6	Good
EE3	0.8	>0.3	>0.6	Good
EE4	0.8	>0.3	>0.6	Good
Latent Variable: Social Influence (SI)				
SI1	0.7	>0.3	>0.6	Good
SI2	0.7	>0.3	>0.6	Good
SI3	0.7	>0.3	>0.6	Good
SI4	0.7	>0.3	>0.6	Good
Latent Variable: Facilitating Conditions (FC)				
OR1	1.1	>0.3	>0.6	Good
OR2	0.8	>0.3	>0.6	Good
OR3	0.7	>0.3	>0.6	Good
OR4	0.8	>0.3	>0.6	Good

Satisfactory factor loadings allowed for the calculation of CR, and all values for TAME exceeded the preferred threshold (Table XXV).

Table XXV. CR Values for the TAME Model

Construct	**CR Value**	**Criteria: Acceptable**	**Criteria: Good**	**Status**
PE	0.860	> 0.6	> 0.8	Good
EE	0.870	> 0.6	> 0.8	Good
SI	0.810	> 0.6	> 0.8	Good
OR	0.923	> 0.6	> 0.8	Good

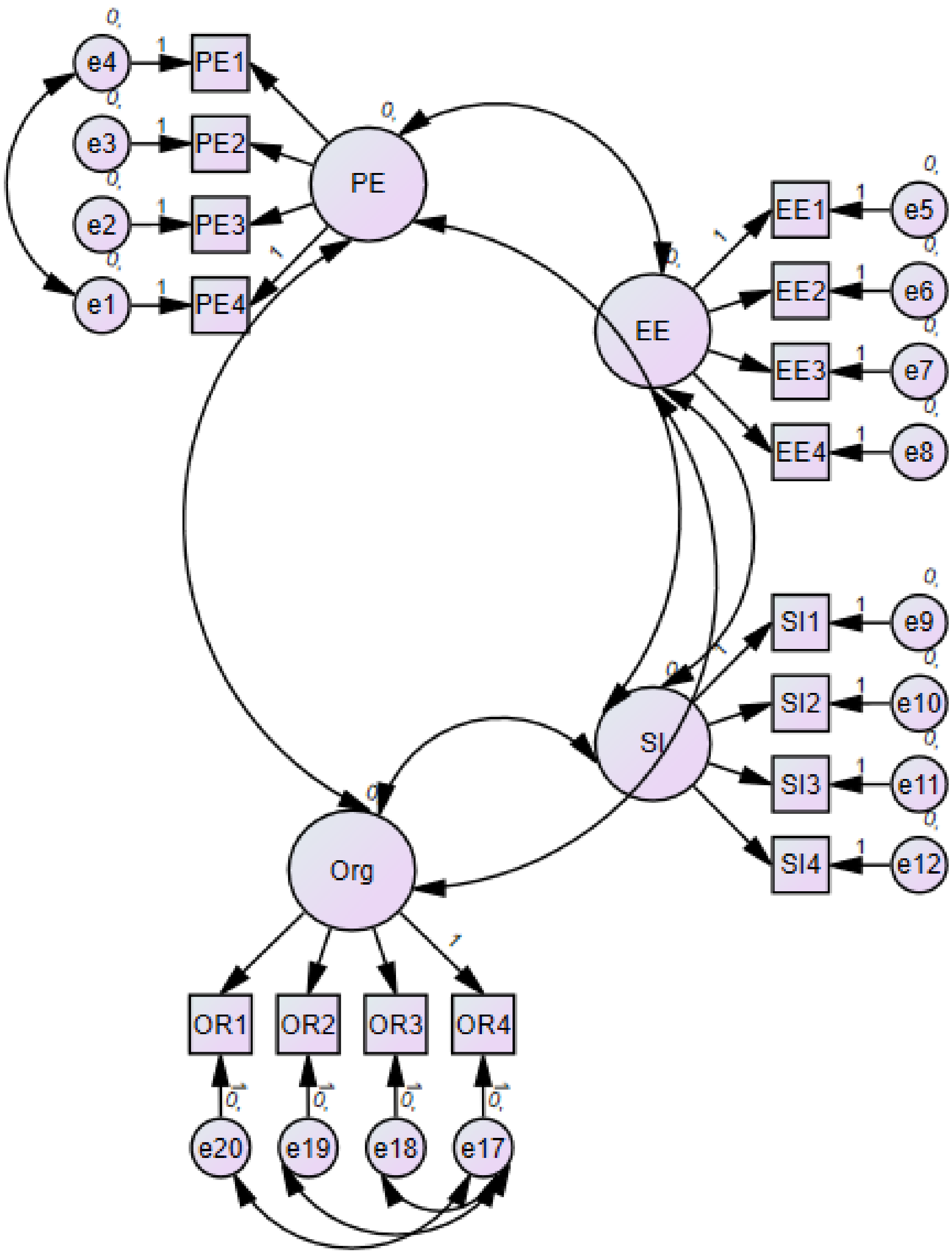

Figure 12. CFA model of TAME

After convergent validity was established, discriminant validity was tested via HTMT. Satisfactory results are reported in Table XXVI, suggesting that each construct is adequately unique to the others.

Table XXVI. HTMT Correlations for the TAME Model

	PE	EE	SI	OR
PE				
EE	0.892			
SI	0.805	0.719		
OR	0.790	0.783	0.814	

5.1.3.3 Structural Equation Modeling

After CFA analysis returned a model with a satisfactory fit of all constructs, an SEM model was created to link the independent variables in the CFA model with the dependent variable BI (Figure 13). RMSEA and CFI results indicated a good model fit and are reported in Table XXVII.

Table XXVII. Fit Indices for TAME

Fit Index	**Value**	**Acceptable Fit**	**Status**
RMSEA	0.067	< .08	Acceptable
CFI	0.946	> .90	Acceptable

After confirming fit indices, factor loadings were calculated for each observed variable in the model to determine whether each survey item adequately contributes to each latent variable (Table XXVIII). All factor loadings met the acceptable criteria, and all but one met the good criteria, indicating a strong relationship between observed and latent variables in the model.

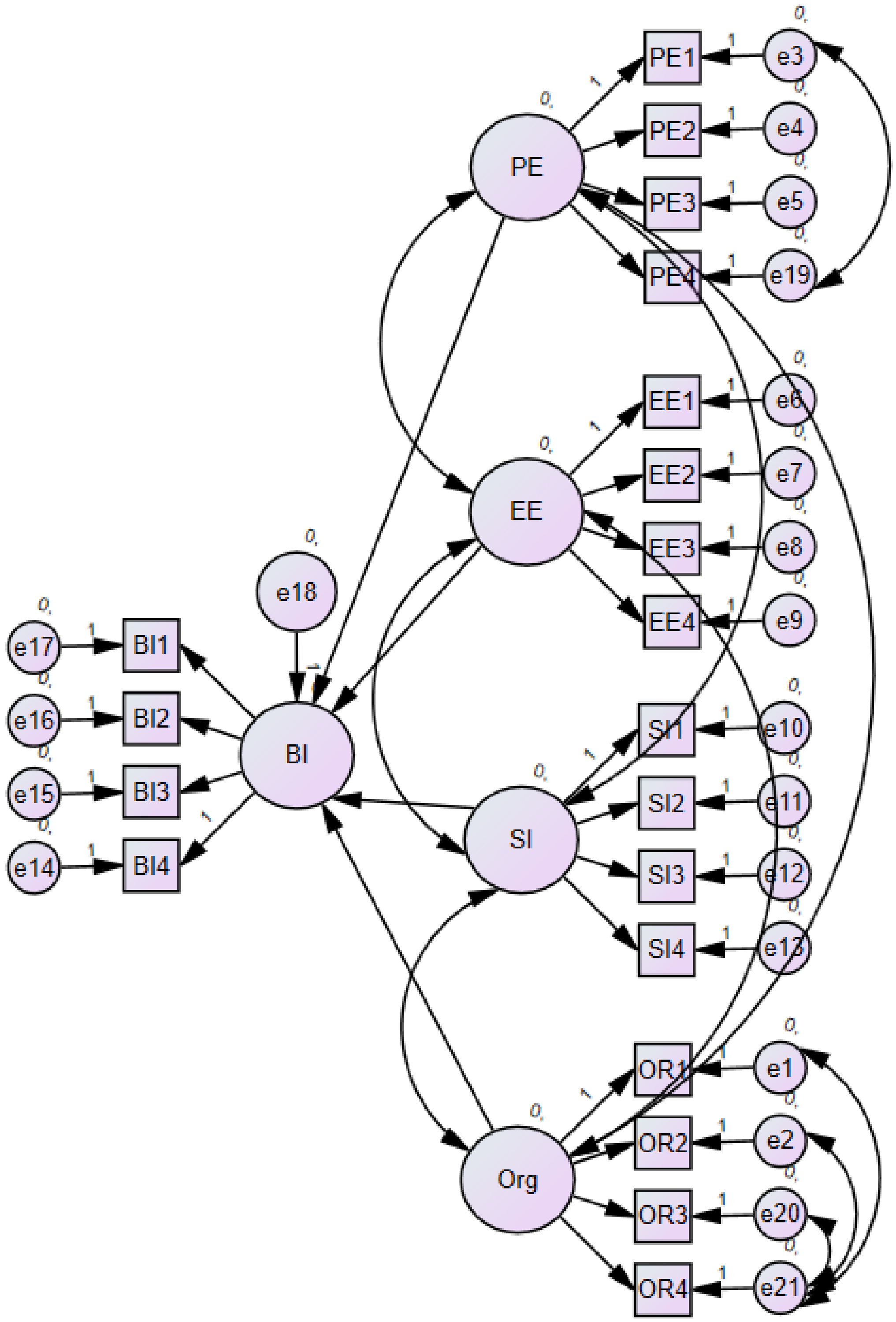

Figure 13. SEM model of TAME

Table XXVIII. Standardized Factor Loadings for the TAME SEM Model

	Factor Loading	**Criteria: Acceptable**	**Criteria: Good**	**Status**
Independent Variable: Performance Expectancy (PE)				
PE1	0.8	>0.3	>0.6	Good
PE2	0.8	>0.3	>0.6	Good
PE3	0.8	>0.3	>0.6	Good
PE4	0.6	>0.3	>0.6	Good
Independent Variable: Effort Expectancy (EE)				
EE1	0.8	>0.3	>0.6	Good
EE2	0.8	>0.3	>0.6	Good
EE3	0.7	>0.3	>0.6	Good
EE4	0.8	>0.3	>0.6	Good
Independent Variable: Social Influence (SI)				
SI1	0.7	>0.3	>0.6	Good
SI2	0.7	>0.3	>0.6	Good
SI3	0.7	>0.3	>0.6	Good
SI4	0.7	>0.3	>0.6	Good
Independent Variable: Organizational Readiness (OR)				
OR1	0.8	>0.3	>0.6	Good
OR2	0.7	>0.3	>0.6	Good
OR3	0.8	>0.3	>0.6	Good
OR4	1.2	>0.3	>0.6	Good
Dependent Variable: Behavioral Intention (BI)				
BI4	0.8	>0.3	>0.6	Good
BI3	0.9	>0.3	>0.6	Good
BI2	0.5	>0.3	>0.6	Acceptable
BI1	0.9	>0.3	>0.6	Good

Finally, relationships between each independent variable and BI were calculated to establish whether significant directional relationships exist where predicted. Values are reported in Table XXIX. PE, EE, and OR were found to have positive and significant relationships with BI, confirming that each construct can predict BI in a pre-implementation context. SI was not found to have a significant effect in the TAME model, meaning that it does not predict BI in a pre-implementation context.

Table XXIX. Relationship Between Independent Variables and BI for TAME

Construct	**Estimate**	**p-value**	**Significant?**
EE	0.463	< .001	Yes
PE	0.480	< .001	Yes
SI	-0.046	0.424	No
OR	0.080	< .001	Yes

The R^2 value for the TAME SEM model was 0.86, indicating that the constructs explain 86% of variance on BI in TAME. This was an improvement relative to the UTAUT model, which had an R^2 of 83%.

5.1.3.4 Moderating Variables

As in the UTAUT analysis, the effects of moderating variables were investigated for TAME. Experience in manufacturing and the interactions of experience*age and experience*gender moderate PE. Gender and the interaction of experience*gender moderate EE. Age and the interactions of experience*age and age*gender moderate OR. Results with significance levels are summarized in Table XXX.

Table XXX. Moderating Variables in TAME

DV: BI	**Exp**	**Age**	**Gender**	**Exp*Age**	**Exp*Gender**	**Age*Gender**
PE	0.0499**	0.6875	0.3133	0.0259**	0.0855*	0.5205
EE	0.1358	0.6608	0.0868*	0.1249	0.0774*	0.2396
OR	0.3075	0.0727*	0.1152	0.0113**	0.3773	0.0649*

*p < 0.1, **p < .05, ***p < .001

The effect of PE, EE, and OR on BI is more salient for women than for men. The data suggest that increasing experience decreases the strength of the positive relationship between PE, EE, and OR with BI, respectively. Increasing age also decreases the effect of PE and OR on BI, but not EE. The correlation between age and experience was 0.729 with a <.001 significance level. The high correlation (and therefore, relatedness) of age and experience may explain the similarities in moderating effects of age and experience on BI. However, the fact that experience and age are significant (or insignificant) for different constructs shows that they have independent moderating effects and should be included as separate moderators even though they are highly correlated.

After moderating effects were obtained, a general model was created to depict TAME in a pre-implementation context for manufacturing (Figure 14).

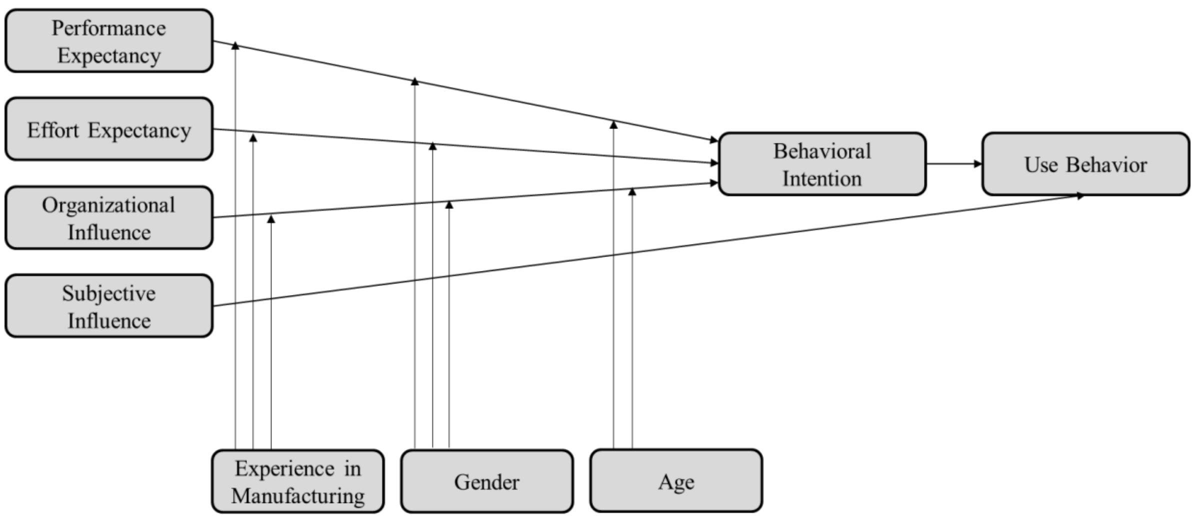

Figure 14. TAME

5.1.4 Exploratory Analysis

Lastly, descriptive statistics and non-parametric tests were conducted to determine whether any notable differences exist between sub-samples of the population. Kolmogorov-Smirnova and Shapiro-Wilk tests confirmed the non-normality of the data (Table XXXI).

Table XXXI. Test for Normality of Data Distribution

Tests of Normality						
	Kolmogorov-Smirnova			**Shapiro-Wilk**		
Construct	**Statistic**	**Df**	**Sig.**	**Statistic**	**Df**	**Sig.**
PE	0.162	823	<.001	0.885	823	<.001
EE	0.145	823	<.001	0.889	823	<.001
SI	0.146	823	<.001	0.924	823	<.001
FC	0.139	823	<.001	0.942	823	<.001
BI	0.199	823	<.001	0.806	823	<.001
OR	0.140	458	<.001	0.820	458	<.001

Box plots were created for each sub-group to conduct visual comparisons, discover outliers, and theoretically interpret findings. For this study, the statistical interpretation of outliers was less important than the theoretical interpretation, so outliers are not reported here. Instead, a summary of categorical comparisons is provided in Table XXXII, and accompanying box plots with outliers may be found in Appendix I.

After the box plot analysis, non-parametric testing was conducted via the Kruskal-Wallis test for multi-group analysis. Where significant differences were found, the Mann-Whitney U test for two independent group testing was conducted to determine which sub-groups have significant differences. Kruskal-Wallis and Mann-Whitney U tests were run with the IBM SPSS Statistics Version 26 software.

Table XXXII. Categorical Comparisons of Sub-Groups

Region	**Location**	**Department**	**Role**	**Age**	**Gender**	**Experience**
United States (US) Mexico (M)	US 1 US 2 US 3 M 1 M 2 M 3 M 4	Machining Stamping Body Paint Final Assembly Logistics Quality Maintenance Engineering	Engineer Front Line Manager	18-24 yrs. 25-34 yrs. 35-44 yrs. 45-54 yrs. 55-64 yrs. 65+ yrs.	Male Female Non-Binary	< 1 yr. 1-3 yrs. 3-5 yrs. 5-10 yrs. 10-15 yrs. 15-20 yrs. 20+ yrs.

Comparison by Region

First, an attempt was made to explore whether any differences between the United States and Mexico exist in the potential technology acceptance readiness of manufacturing employees. Statistically significant differences were found for the two regions for the constructs PE, EE, FC, and BI. Significant differences and means for each construct are reported in Table XXXIII, suggesting that Mexico has a higher rate of technology acceptance than the United States.

Table XXXIII. Means and Statistical Differences by Region

Construct/Region	United States	Mexico	Significance
PE (μ)	4.97	5.73	<.001
EE (μ)	5.40	5.71	<.001
SI (μ)	5.17	5.27	.081
FC (μ)	4.83	5.11	<.001
BI (μ)	5.70	5.91	<.001

Comparison by Location

Locations of each region were compared next. Regional facilities in different parts of each country (i.e., urban versus rural) may vary by ethnicity, population size, and affluence. The means and statistical difference findings for each construct are reported in Table XXXIV.

Table XXXIV. Means and Statistical Differences by Location

Construct/Location	US 1	US 2	US 3	M 1	M 2	M 3	M 4	Sig.
PE (μ)	5.04	4.92	4.94	5.67	5.66	6.16	5.38	<.001
EE (μ)	5.50	5.40	5.32	5.71	5.52	6.07	5.40	<.001
SI (μ)	5.14	5.19	5.19	5.23	5.31	5.46	4.96	.223
FC (μ)	4.81	4.85	4.82	5.13	5.13	5.06	4.85	.004
BI (μ)	5.77	5.58	5.71	5.87	5.81	6.33	5.46	<.001
OR (μ)	N/A	N/A	N/A	5.27	5.29	5.40	4.60	.421

Upon further analysis via Mann-Whitney U tests, significant differences exist for multiple locations. Results are summarized in Table XXXV. Results indicate that no US locations are statistically similar to M locations for any construct, re-confirming regional findings at the individual location level. Statistical differences were found between the United States and Mexican locations for PE, EE, FC, and BI, similar to findings on regional differences. M locations 1, 2, and 4 were statistically similar to one another, but M 3 differed statistically from M 1 and M 2 in PE, EE, and BI.

Table XXXV. Mann-Whitney U Test Results by Location

	US 1	**US 2**	**US 3**	**M 1**	**M 2**	**M 3**
US 2	--					
US 3	--	--				

M 1	PE, EE, FC	PE, EE, FC	PE, EE, FC			
M 2	PE, FC	PE, FC	PE, FC	--		
M 3	PE, EE, SI, FC, BI	PE, EE, SI, BI	PE, EE, SI, FC, BI	PE, EE, BI	PE, EE, BI	
M 4	PE	PE	PE	--	--	--

Comparison by Department

Various departments in manufacturing are responsible for different parts of the manufacturing process. For example, Body Shop has more autonomous equipment where parts are welded together, whereas Final Assembly has many more employees performing manual parts installations. To better understand the technology acceptance levels of each department for comparison, means and statistical differences were calculated (Table XXXVI). Significant differences were found for PE and FC.

Table XXXVI. Means and Statistical Differences by Department

Construct/ Department	**Assembly**	**Body**	**Stamping**	**Paint**	**Logistics**	**Quality**	**Maintenance**	**Engineering**	**Significance**
PE (µ)	5.18	5.67	5.37	5.58	5.37	5.55	5.44	5.19	.013
EE (µ)	5.34	5.81	5.43	5.59	5.52	5.57	5.56	5.60	.360
SI (µ)	5.20	5.34	5.20	5.18	5.16	5.41	5.27	5.14	.585
FC (µ)	4.84	5.35	5.14	5.05	4.88	4.97	5.08	4.84	.033
BI (µ)	5.59	6.10	5.79	5.84	5.76	5.92	5.76	5.81	.204
OR (µ)	5.25	5.38	5.26	5.16	5.21	5.51	5.28	5.15	.732

After additional analysis (summarized in Table XXXVII), it was found that Body Shop differed from Final Assembly in PE and FC, and Logistics in FC. Engineering was significantly different from Body Shop, Paint, Quality, and Maintenance in PE, and Body Shop and Maintenance in FC.

Table XXXVII. Mann-Whitney U Test Results by Department

	Assembly	Body	Stamping	Paint	Logistics	Quality	Maint.
Body	PE, FC						
Stamping	--	--					
Paint	--	--	--				
Logistics	--	FC	--	--			
Quality	--	--	--	--	--		
Maint.	--	--	--	--	--	--	
Eng.	--	PE, FC	--	PE	--	PE	PE, FC

Comparison by Role

Like each department, various job positions or roles may interact differently with new technologies. For example, the engineering department may be responsible for selecting new technologies, managers may be responsible for training and enforcement of new technologies, and front-line employees may be end users of the technology on the job where it is implemented. Due to the varying responsibilities by role in the company, testing was done on means and significant differences (Table XXXVIII). A significant difference was found for PE.

Table XXXVIII. Means and Statistical Differences by Role

Construct/Role	Engineer	Front Line	Manager	Sig.
PE (μ)	5.28	5.44	5.38	.041
EE (μ)	5.60	5.51	5.58	.463
SI (μ)	5.20	5.13	5.31	.054
FC (μ)	4.92	5.04	4.97	.454
BI (μ)	5.88	5.70	5.85	.172
OR (μ)	5.09	5.29	5.33	.457

Mann-Whitney U tests indicated that Engineering and Front-Line workers differ in PE. No differences between Management and either Engineering or Front-Line workers were found.

Comparison by Age

Considering that Venkatesh et al. (2003) discovered age as a moderating variable in several UTAUT constructs, it was decided to compare results by age. Results of TAME indicated moderating effects of age, which supports the continued exploration by comparison testing.

Table XXXIX contains a comparison of means and results of Kruskal-Wallis testing by age, where PE, EE, and BI differed. Mann-Whitney U testing was done for all age brackets, and the results are summarized in Table XL.

Table XXXIX. Means and Statistical Differences by Age

Construct/Age	**18-24**	**25-34**	**35-44**	**45-54**	**55-64**	**65+**	**Sig.**
PE (μ)	5.53	5.69	5.44	4.96	5.35	5.00	<.001
EE (μ)	5.55	5.83	5.62	5.29	5.42	5.25	<.001
SI (μ)	5.35	5.30	5.27	5.03	5.38	5.00	.066
FC (μ)	5.19	5.09	5.06	4.73	5.02	4.75	.068
BI (μ)	5.88	6.03	5.89	5.50	5.85	5.08	<.001
OR (μ)	5.58	5.16	5.43	5.06	5.98	N/A	.074

Table XL. Mann-Whitney U Test Results: Statistical Differences by Age Bracket

	18-24	**25-34**	**35-44**	**45-54**	**55-64**
25-34	--				
35-44	--	PE, EE, BI			
45-54	PE	PE, EE, BI	PE, EE, BI		
55-64	--	PE, EE, BI	--	--	
65+	--	--	--	--	--

The 25–34-year-old age bracket differed from the most other age brackets, with significant differences reported in PE, EE, and BI between 25-34 years old, 35-55 years old, 45-54 years old, and 55-64 years old. PE, EE, and BI also differed significantly for ages 35-44 and 45-54.

Comparison by Gender

Venkatesh et al. (2003) reported a moderating effect for age in UTAUT. When tested for TAME, gender did not moderate any constructs. Mean comparisons and Kruskal-Wallis results by construct are summarized in Table XLI.

Table XLI. Means and Statistical Differences by Gender

Construct/Gender	**Male**	**Female**	**Non-Binary**	**Sig.**
PE (μ)	5.36	5.44	5.58	.499
EE (μ)	5.56	5.60	6.58	.177
SI (μ)	5.23	5.17	5.00	.939
FC (μ)	5.00	4.84	4.25	.484
BI (μ)	5.81	5.82	6.33	.345
OR (μ)	5.28	5.21	4.50	.346

Due to no statistical differences found in the Kruskal-Wallis test, Mann-Whitney U tests were not conducted for the three gender groups.

Comparison by Experience

A level of experience in the manufacturing domain also has the potential to affect constructs in TAME. As experience increases, job and process knowledge should also increase. This may have a positive or negative effect on technology acceptance. The results of the testing are summarized in Table XLII. Differences were found for PE, EE, FC, and BI, which were further explored via Mann-Whitney U tests (Table XLIII).

Table XLII. Means and Statistical Differences by Experience

Construct/ Experience	**<1 yr.**	**1-3 yrs.**	**3-5 yrs.**	**5-10 yrs.**	**10-15 yrs.**	**15-20 yrs.**	**20+ yrs.**	**Sig.**
PE (μ)	5.63	5.39	5.61	5.67	5.34	5.45	5.08	<.001
EE(μ)	5.38	5.64	5.82	5.78	5.63	5.64	5.31	<.001
SI (μ)	5.33	5.33	5.24	5.36	5.15	5.37	5.07	.090
FC (μ)	5.25	4.77	5.10	5.23	4.92	5.02	4.82	.038
BI (μ)	6.29	5.72	5.84	6.01	5.97	5.97	5.54	<.001
OR (μ)	5.95	5.55	5.36	5.19	5.09	5.45	5.26	.681

Table XLIII. Mann-Whitney U Test Results by Experience

	<1 yr.	1-3 yrs.	3-5 yrs.	5-10 yrs.	10-15 yrs.	15-20 yrs.
1-3 yrs.	--					
3-5 yrs.	--	--				
5-10 yrs.	--	--	--			
10-15 yrs.	--	--	--	--		
15-20 yrs.	--	--	--	--	--	
20+ yrs.	--	--	PE, EE	PE, EE, FC, BI	PE, EE, BI	PE, EE, BI

The group with 20+ years of experience differed significantly on multiple constructs from those with 3-20 years of experience but not from those with 0-3 years of experience.

5.1.4.1 Effect Sizes

Of seventy-seven statistical differences found for various constructs and groups in Mann-Whitney U tests, sixty-six were small ($r < 0.3$), eleven were medium ($0.3 < r < 0.5$), and none were large ($r > 0.5$). All effects above 0.3 were in the Region and Location categories and are reported in Table XLIV.

Table XLIV. Group Comparison Effect Sizes

Construct	Two Groups	Z	N	Effect Size
Region				
PE	US x M	9.379	823	0.327
Location				
PE	US 1 x M 3	6.294	188	0.459
EE	US 1 x M 3	4.132	188	0.301
PE	US 2 x M 2	4.197	195	0.301
PE	US 2 x M 3	5.979	180	0.446
EE	US 2 x M 3	4.107	180	0.306
BI	US 2 x M 3	4.475	180	0.334
PE	US 3 x M 2	4.914	231	0.323
PE	US 3 x M 3	7.131	216	0.485
EE	US 3 x M 3	4.976	216	0.339
BI	US 3 x M 3	4.780	216	0.325

5.1.4.2 Multi-Factor Interactions

Location and Department

Two-way and three-way ANOVA tests were conducted for each possible interaction of demographic groups for each construct, totaling 285 different tests. Results are summarized in Table XLV. One asterisk denotes a small effect size, and two asterisks denote a medium effect size. No large effects were found.

Table XLV. ANOVA Results for Multi-Factor Interaction Effects

Construct	**PE**	**EE**	**SI**	**FC**	**OR**	**BI**
Location, Role	0.781	0.418	0.050	0.254	0.035*	0.680
Location, Experience	0.540	0.854	0.095	0.336	0.020**	0.606
Location, Age	0.019*	0.182	0.045*	0.102	0.009*	0.012*
Department, Age	0.775	0.334	0.242	0.201	0.012**	0.109
Role, Age	0.130	0.195	0.693	0.111	0.182	0.022*
Experience, Age	0.348	0.040*	0.703	0.015*	0.730	0.389
Region, Age, Experience	0.531	0.351	0.037*	0.573	N/A	0.728
Location, Department, Age	0.58	0.143	0.272	0.867	0.911	0.019**
Location, Role, Experience	0.104	0.063	0.146	0.493	0.042**	0.014**
Department, Role, Age	0.023**	0.183	0.444	0.635	0.089	0.045**

Chapter 6: Discussion

I4.0 presents opportunities for manufacturing for increased capability and efficiency. However, research on integrating I4.0 with the workforce is lacking. In choosing which technologies to implement, the human component must be considered. Using TAME may help employers gauge employees' readiness to accept a new technology before making an implementation decision. Pre-implementation surveying allows employers to identify gaps in readiness to accept new technologies before launch and mitigate employee concerns so that they are bought into the idea of a new technology before it reaches them, thereby reducing risks in the technology implementation initiative. Risk mitigation will increase the chances of a successful technology launch and may increase employee openness toward new technologies.

Existing technology acceptance models were created with the individual or organization in mind. Individual technology acceptance models do not comprehensively consider a context where the individual surveyed may be a part of a company and, therefore, not the end-decision maker. Additionally, individual employees may not have control over the implementation process, and a lack of confidence in the organization can lead to failed implementation. Employees' reliance on the organization for implementation leads to a need for organizations to know whether employees feel that it is ready to implement new technologies. On the other hand, existing organizational technology acceptance models are too narrow in scope to be applied to individual employees. Many organizational technology acceptance models focus on metrics relevant to decision-makers but not the working-level employees interacting with the technology.

Available technology acceptance models have been created for a current or post-use implementation context and have not been applied to a pre-implementation context. Research in manufacturing contexts is also limited. Manufacturing organizations must have an appropriate measure for pre-implementation, as this is a critical stage in integrating I4.0 and the manufacturing workforce. Attempting implementation before buy-in from employees can lead to a delay in implementation or even failure to implement the new technology, which wastes organizational resources and negatively affects employee perception of new technologies.

6.1 Pilot Phase Discussion

An initial study of a new technology acceptance model that considers organizational and individual constructs (TAME) suggested that the new measure is more appropriate for a pre-implementation manufacturing context than currently available technology acceptance models. Results indicated that each construct included in TAME was sufficiently unique. Internal reliability scores provide support for the use of the survey instrument created for TAME. This initial study also supported hypothesis H_1, that organizational readiness is a separate, useful construct in gauging individual employee technology acceptance.

Cronbach's alpha and inter-item correlation scores confirm the viability of constructs included in the survey instrument, providing evidence that the instrument is appropriate for its intended use. Cronbach's alpha scores for two of the constructs did not meet the recommended threshold of 0.7. However, inter-item correlation scores, an alternative to Cronbach's alpha for survey instruments with small sample sizes, met the recommended range of 0.2-0.4, suggesting the two constructs with low Cronbach's alpha scores had acceptable reliability. The fact that the Cronbach's alpha scores for two constructs did not meet the acceptable threshold may have been due to the small sample size and/or having fewer than ten statements per construct, which are common contributors to low Cronbach's alpha scores (Pallant, 2016). In their study of UTAUT with a larger sample size (N=215), Venkatesh et al. (2003) found that all main constructs scored 0.7 or above. Since the current study retains the intent of each UTAUT statement, it was determined that increasing the sample size and/or incorporating more of the original UTAUT statements will increase the instrument's internal consistency. Similarly, Shea et al. (2014) reported strong internal reliability scores of 0.8 or above in their proposal of the constructs in ORIC. When consolidated into three statements for the OR component of TAME, the Cronbach’s alpha score was below the acceptable threshold, although the inter-item correlation was acceptable. It was determined that consolidating the ORIC survey instrument may have resulted in a lower Cronbach’s alpha score, and an additional item was included in the OR construct for the full-scale phase.

In addition to statistical measures, participant feedback was collected for suggested changes to the survey instrument. Other than a few minor wording and format changes, there were two feedback suggestions of note. First, the suggestion was made to include a video as a description to provide a visual representation of the technology being surveyed. Participants felt that the short paragraph of information was insufficient to communicate possible technology uses adequately. After consideration, it was decided that incorporating a video in the instrument could assist participants in learning about possible applications without providing any training that would negate the pre-implementation context. The second suggested modification was to replace the specific referenced technology (Google Glass) with the term AR, encompassing more applications and reaching a wider potential use audience. The modification of the referenced technology from Google Glass to AR was therefore also incorporated into the second phase of the study.

6.2 Full-Scale Phase Discussion

6.2.1 Improvements from the Pilot Phase

After changes to the pilot survey instrument were made, it was disseminated to the sample population for a full-scale study. When tested with a larger sample in the target population, TAME constructs each met the acceptable reliability threshold. Internal reliability results for PE, EE, SI, and FC from the full-scale phase were similar to those reported by Venkatesh et al. (2003) in their study proposing UTAUT. The reliability score for OR more closely reflected scores reported for ORIC. The strong internal reliability score for OR in the full study suggests that the additional survey item and larger sample size improved OR's robustness when tested for pre-technology implementation in a manufacturing environment. These results were encouraging as the TAME survey instrument aimed to alter statements only for a pre-implementation context and retain the intention of statements on the UTAUT instrument. Reliability scores from the full-scale phase indicate that each construct in UTAUT behaves the same way in a post-implementation and pre-implementation context, supporting the use of UTAUT in a pre-implementation context.

6.2.2 Objective 1: Validate UTAUT in Pre-Implementation Context

A thorough validation was conducted on the UTAUT instrument in a manufacturing, pre-implementation context, achieving Objective 1 and confirming the null hypothesis H_0. All statistical testing results support the use of UTAUT as a good model fit. However, one major difference was found between Venkatesh et al.'s (2003) results and the results of this study. The insignificance of SI in predicting BI was different from the original UTAUT proposal study by Venkatesh et al. (2003). The FC result was similar to Venkatesh et al. (2003), who found that FC was not significant in predicting BI but in predicting actual use.

While the result for FC was not surprising (Venkatesh et al. (2003) also found FC to be insignificant in predicting BI), the result for SI requires interpretation. The survey items for SI intend to capture the amount of influence an individual perceives others have on his or her use of the technology. If SI does not significantly predict BI, this suggests that outside influences on the individual do not affect that person's level of technology acceptance. Whether a peer, authority figure, or the organization would want the individual to accept the technology does not appear to have a significant bearing on that person's intention to use it.

In the manufacturing industry, employees do not have final decision-making power on technology implementation. Instead, depending on a person's role within the company, he or she may provide a business case to executive decision makers for a certain technology, lead or assist with implementation, or be an end user of the technology. Whether the employee feels their peer group or manager would want to implement the technology may not necessarily be relevant to acceptance. The SI construct is, therefore, likely more relevant to an individual consumer than in an organizational context.

Another explanation may be that the pre-implementation phase is too early to examine the relationship between SI and BI adequately. Suppose an employee has no experience with a new technology. In that case, as in a pre-implementation context, that individual may not have enough information to know whether others would want him or her to use the technology. This may explain why Venkatesh et al. (2003) found a significant relationship between SI and BI in a post-implementation context.

6.2.3 Objective 2: Validate TAME and Compare to UTAUT

As with the validation of UTAUT, statistical testing revealed that TAME is also a valid model for gauging the technology acceptance of employees in a pre-implementation manufacturing context. However, data suggests that TAME is the stronger of the two models. During validation, it was determined that PE, EE, and OR significantly predict BI for TAME. The CFA model could not be appropriately fit with FC in it. An appropriate fit with SI was achieved in the CFA, but SEM modeling suggested that SI is insignificant in predicting BI.

Several possible explanations exist for the low contribution level of SI and FC to the TAME model. Possibilities as to the insignificance of SI and FC are discussed in Section 6.2.2, where the same result was found for the UTAUT model. However, FC being excluded at the CFA level from the TAME model bears additional exploration. It was anticipated that FC might not be significant at the SEM stage, as this is the phase where independent variable constructs are applied to the dependent variable BI. When creating the CFA model, the latent constructs PE, EE, SI, OR, and FC were correlated with one another and with their observed variables (i.e., individual survey items). Correlating each latent construct with other latent constructs tests for expected relatedness of constructs. Correlating each latent construct with its observed variables establishes that each latent construct is adequately described by the survey items corresponding to it. With FC as a part of the model, an appropriate fit was not achieved. This may be due to FC being too close in nature to another latent variable, decreasing its contributory power to the model. The construct closest to FC in TAME is OR. While FC describes the actual resource availability and compatibility of the new technology with existing technologies OR describes the organization’s willingness and ability to devote resources and support the implementation of new technology. While technically different, these two constructs could be related enough to challenge one another statistically. Interestingly, in this study, the only difference between the UTAUT CFA model – which did obtain an adequate fit with FC – and the TAME CFA model, where FC was rejected, is the addition of OR. However, while FC was found to be insignificant in the UTAUT SEM model, OR was found to be significant in the TAME SEM model. This finding suggests that the OR construct more adequately represents the data in this study than FC.

While FC and SI were not found to be significant in the model, it may be useful to leave them in TAME for a few reasons. First, the current research did not collect actual use data. While insignificant to BI, it is possible that either FC or SI could be significant to actual use in a longitudinal or post-implementation study. Also, while these constructs do not technically add to the statistical power of the model, the answers to the questions may still provide insight for organizations. For example, it may be useful to the organization to know whether an employee believes his or her peers would want him or her to use a new technology. This can help pinpoint where more positive or negative workgroups exist in the manufacturing process, giving organizations a chance to either implement new technologies with the more positive workgroups or build up confidence in the new technology in negative workgroups prior to implementation.

Additionally, the TAME SEM model explained more of the variance in BI than the UTAUT SEM model. The higher value suggests that more of the explanation for what constructs affect BI is covered by TAME, leading to the conclusion that TAME is more appropriate than UTAUT in gauging employee technology acceptance in a pre-implementation manufacturing context. Therefore, Objective 2 is achieved, and the alternate hypothesis $H_{1'}$ is accepted.

6.2.4 Objective 3: Explore Significant Differences Between Groups

Comparison by Region

One of the first comparisons was between the United States and Mexican regions. These regions have different leadership work streams in the organization being studied, converging at Senior Vice President (SVP). Up to six levels of management below the SVP are allocated to either the United States or Mexico. According to Metcalfe (2008), differences may occur across countries due to wealth accumulation, rate of economic growth, technology, and the creation of and interaction among institutions. Edquist (2005) describes institutions as “sets of common habits, norms, routines, established practices, rules, or laws that regulate the relations and interactions between individuals, groups, and organizations.” Various literature reports differences between the United States and Mexico specifically. These include family support system (Falicov, 2000; Strong & Cohen, 2013), views on increased work hours (Falicov, 2000; Okulicz-Kozaryn, 2011), individualism (Triandis et al., 1988), religion (Weber, 1930), and opportunity for social mobility (Alesina et al., 2004). This study attempted to explore whether differences between the United States and Mexico exist in the technology acceptance of manufacturing employees.

Through Kruskal-Wallis and Mann-Whitney U testing, statistical differences across the two regions were found for PE, EE, FC, and BI. There was no statistical difference found for SI. This suggests that employees in the United States and Mexico differ in their opinions on how much efficiency the technology will add to the job, how easy it will be to use, the available resources, and how well the technology will integrate into existing systems. Of key importance, the two regions differ in overall intention to use the technology. Comparing means for each construct shows that Mexico has a higher overall acceptance level of overall technology than the United States. This may be an important finding for the organization. It could choose to implement new technologies in Mexico first, where it is likely to be more successful, then cross-deploy the technology to the United States after proof of concept is obtained. This could help persuade employees in the United States to accept the new technology if they first see the benefits in Mexico. On the other hand, if the new technology implementation fails, Mexico may be less discouraged toward continuing to try new technologies in the future.

If the organization wishes to implement new technology in the United States first, it has some useful information about where it can bolster implementation efforts. It can ensure that employees are aware of all possible uses of the new technology, potentially increasing PE. It can also provide adequate training and support before and during implementation, which could lead to increased EE and FC. Increasing PE and EE should thereby increase BI, as the results of this study show a positive relationship between PE and EE as antecedents of BI.

Comparison by Location

After overall regional differences were explored, comparisons were performed by locations within each region. No statistical differences were found among the three United States locations studied. This may be because they are all within the same geographical area of the country (the Southeast) or because all three plants are about the same distance from a large city. Data from the U.S. Census Bureau indicates that the three cities in which the facilities are located have a similar distribution of age, gender, and level of education (U.S. Census Bureau, 2021). These similarities may contribute to the uniformity of responses from the U.S. locations.

Alternately, significant differences between PE, EE, and BI were found for one Mexican facility compared to the other three (M 3). This facility was unique to the others because it is close to the country's capital and largest city. M 1, M 2, and M 4 are in a much more rural area. This means that the employee population at M 3 may be demographically different from employee populations in other cities. Overall, technology acceptance is higher for M 3, the facility nearer to the large city. An interesting note is that M 3 is much older than the others and may not have the updated technologies typically present in newer facilities. Indeed, M 3 scored lower on FC than M 1 and M 2. However, M 3 scored higher than any other location on PE, EE, and BI, indicating that employees there feel technology improvements will help them do their jobs and are open to trying new technologies. Employees here may be more open to new technologies because they feel their facility lags behind others.

The organization may use this information the same way it can from the regional comparison. However, paying attention to FC at the older, unique Mexican facility may be of particular importance if its systems and resources cannot support newer technologies.

Comparison by Department

Next, departments were compared. The main finding from this comparison was the difference between Engineering and most other departments. Statistically significant differences in PE were found between Engineering and four of the seven other departments studied (Body Shop, Paint Shop, Quality, and Maintenance). Statistically significant differences in FC were also found between Engineering and Body Shop and Engineering and Maintenance. Few statistical differences were found among the other departments, which is an important finding. This points to a possible disconnect between the Engineering department – often responsible for research, selection, and implementation of new technologies – and the departments that would be potential end-users.

When means for each construct were analyzed, it was found that the Engineering department scored PE and FC lower than the other departments, suggesting that Engineering does not believe AR will enhance job performance as much as other departments do and that Engineering does not believe the organization has the resources nor support structure to implement AR. Pfeiffer (2016) reports that employees are often subject matter experts, and at the particular organization studied, engineers are responsible for researching and integrating new technology in the facility. The lower score for PE may be because engineers in this organization are aware of various technologies on the market and may think there are better options for the manufacturing process than those shown in the introductory material for the survey. Alternately, engineers may feel that AR will not improve job efficiency as much as promised by the technology proponents.

Similarly, the lower score for FC suggests that engineers have greater concerns than other departments that the organization has the infrastructure to support the implementation of AR. The organization can explore engineers' possible concerns further with tools such as focus group feedback or soliciting anonymous suggestions. Soliciting employee feedback allows the organization to discover where FC is lacking and make improvements before attempting AR implementation. The role of the Engineering Department at different organizations may vary, so this finding is not necessarily representative of all engineers. Organizations should consider the roles and responsibilities of each department involved in technology implementation when applying the TAME model.

Comparison by Role

Role comparisons revealed a statistically significant difference in PE between front-line workers and engineers. Front-line workers were found to have a higher perception of PE than engineers or managers when compared side by side in box plots. However, the difference between engineers and managers was not statistically significant. The higher score for PE in front-line workers indicates an optimism toward new technologies helping to increase job efficiency. This is a promising finding for the organization because it suggests that employees who would be end users of this technology believe in its ability to help them do their jobs.

No differences were found between managers and either front-line workers or engineers. This is interesting because managers are often in a liaison role when it comes to process changes (Cieślińska, 2007) and therefore new technology implementation. Managers support engineers as they research, choose, and implement new technologies. They also support front-line workers by ensuring adequate training and time to learn the new technology during and after implementation. The fact that there is a significant difference between front-line workers and engineers, but not between managers and either of the other two groups, further supports the idea of managers existing in an in-between role, working with both groups in the interest of the organization as a whole.

Comparison by Age

Age comparisons revealed a difference primarily between the age bracket 25-34 years old and the others. PE, EE, and BI were found to be significantly different between the 25–34-year age bracket and the 35-44-, 45-54-, and 55–64-year-old age brackets. Additionally, the 35–44-year-old age bracket was found to be different from the 45–54-year age bracket in PE, EE, and BI. This finding was of interest because the significant differences were found at a generational transition point. While the 25–34-year-old age group primarily consists of Millennials, the 35–54-year-old age bracket primarily consists of Gen X, and the 55–64-year-old age bracket consists of Baby Boomers. When means were compared, Millennials appeared to be more accepting of new technology than the other two generations, which is consistent with general findings in the literature (Murray, 2011).

It is also worth noting that while results for all age groups were overall positive toward technology acceptance, there were more low-scoring outliers in older age groups than groups representing younger generations. This could be a positive finding for the organization, as it can determine which groups the outliers belong to and establish what is causing the negative views of these select few individuals. The organization may be able to increase these individuals' acceptance levels, or it may find out an important piece of information it was not previously aware of that genuinely affects the performance capabilities of the new technology being studied.

Comparison by Gender

Contrary to findings by Venkatesh et al. (2003), gender did not moderate any relationships between various model constructs and BI. This finding could be because fewer women and non-binary individuals responded to the survey than men, so the proportions for comparison differed greatly. However, the proportions were relatively similar to the gender breakdown of the target population. Many more males work in the manufacturing domain than females, which makes the industry different from others, such as business or healthcare, where UTAUT had previously been applied. This study presents the first known data on moderating effects of gender in a manufacturing technology acceptance model. It is important to note that gender does not appear to play a role in BI for manufacturing in a pre-implementation context, so the proportion of male, female, and non-binary employees should not affect the level of technology acceptance for the work group being surveyed.

Comparison by Experience

Lastly, comparisons by experience were made to determine where significant differences exist, if any. Surprisingly, it was found that no difference existed between any levels of experience except 20+ years. The 20+ year experience bracket differed significantly in PE and EE from experience brackets between 3-20 years, BI from brackets between 5-20 years, and FC from the 5–10-year bracket. The corresponding box plots show that the overall technology acceptance of employees with 20+ years of experience is lower than their counterparts. This may be due to comfortability with the manufacturing processes as they currently are or resistance to new technology in general. Naturally, employees with increasing years of experience will also be older, so seeing a similar pattern to the age groups (decreased technology acceptance with increased age) is not surprising. Organizations must consider the opinions of their most experienced employees, as they may be the unofficial 'group leaders' whom younger and less experienced employees look to in uncertain situations. If these employees do not buy into new technology implementation, they may influence other employees who are neutral or undecided, bringing the overall chances of a successful implementation down. However, due to their experience, these employees can also counterbalance organizations trying to implement new technologies just for the sake of implementation. If the new technology is not the best for the organization, these employees may be able to explain how the current process is adequate.

In summary, many significant differences exist between sample sub-groups, indicating that an individual's demographics affect BI in a pre-implementation manufacturing context. Therefore, the alternate hypothesis H_{1}" is accepted.

Effect Sizes

Although there were seventy-seven statistical differences found in various sample groups, sixty-six were determined to be small in magnitude. None of the differences were determined to be large, and eleven were medium. The eleven differences that were medium in magnitude occurred in the Region and Location groups. This indicates that the largest discrepancy between sub-groups occurred in different locations of the employer. The differences between other demographics, such as Age, Experience, and Department, were not as widespread. The fact that the regions and locations saw the largest differences means that organizations need to be particularly cognizant of possible differences in their facilities and the factors that may contribute to varying levels of technology acceptance from one facility to the next.

Multi-Factor Interactions

Out of 285 ANOVA tests, nine statistical differences of small magnitude were found, seven statistical differences of medium magnitude were found, and no differences of large magnitude were found. The small proportion of statistical differences, and the fact that none were large differences, indicates that the sample tested did not vary widely in levels of technology acceptance regardless of the various demographic factors present.

The lower number of interaction effects when compared to the number of main effects found indicates that demographic factors independently affect levels of technology acceptance more than the interaction of any two or three combined factors. For example, the lack of significance of the interaction between location*department means that the location or department itself (i.e., the main effect) has more influence on each construct than the combination of the two. In practical terms, this means that while Engineering as a collective has statistically significant different scores for PE than the Body, Paint, Quality, and Maintenance departments, the Engineering departments at various locations do not have statistically different views on any construct.

6.2.5 Outliers

It is worth noting that almost all box plots had multiple outliers with unusually low scores compared to overall high levels of acceptance otherwise. These outliers provide a unique insight not otherwise highlighted by statistical analysis of the model. Essentially, these outliers are the employees who may roadblock the implementation process. They are the employees who may not be interested in implementing any new technology regardless of potential benefit. They may feel the organization is unprepared or unwilling to provide adequate support for implementation. They may have been part of an implementation initiative in the past that was unsuccessful and are now skeptical of any new technologies. Regardless of the reason, in a real-world application of TAME, an organization could determine where these employees work within the facility and work toward garnering more support. This may be accomplished by asking for feedback, as Sirkin et al. (2005) suggested. It may require the presentation of a sufficient business case, a demonstration of that technology being used on a similar job, or even taking suggestions on alternate technologies that could be implemented in place of the one suggested by the organization.

The fact that most employees had an overall positive level of acceptance (scoring somewhere between ‘neutral’ and ‘strongly agree’ on each construct) is an encouraging finding both for the organization where the study was conducted and for the implementation of I4.0 technologies in manufacturing. However, outliers must be addressed to avoid possible challenges in implementation from the few negative opinions.

Chapter 7 Conclusions

This dissertation aimed to develop a technology acceptance model with applicability to a large-scale manufacturer in a pre-implementation context, determine whether perception of the organization's readiness affects technology acceptance for individual employees, and explore whether gaps in acceptance levels exist between various sub-groups of the collected sample. After thoroughly reviewing available technology acceptance models, the UTAUT model was chosen to assess applicability in a pre-implementation manufacturing context. A latent variable describing organizational readiness to implement new technologies was added to UTAUT, resulting in the TAME instrument. An initial study of TAME confirmed internal reliability and face validity, proving its viability as a more robust model for pre-implementation in manufacturing organizations than the UTAUT model alone.

Reliability results from the pilot data were adequate but not as strong as expected, given results from the UTAUT and ORIC instruments alone in previous research. After lengthening the survey for the full-scale phase, reliability results improved. Future work should consider the effects of a shorter survey instrument on internal reliability. The balance of creating a comprehensive survey instrument while considering the length of time required to complete the study should be weighed carefully.

After modifications to the initial survey instrument, the TAME instrument, including UTAUT constructs, was disseminated to a substantial sample of a large-scale manufacturers with locations in both the United States and Mexico. Data were first used to validate the UTAUT model for a manufacturing, pre-implementation context. CFA modeling was conducted to assess model fit and establish construct validity. Then, SEM modeling was used to confirm the directional relationships of each latent variable with BI. PE and EE were strong predictors of BI, but SI and FC did not strongly affect BI. The insignificance of SI and FC in predicting BI for a pre-implementation context supports the possibility of additional constructs adding insight to the model and explaining more of the relationship to BI. The full TAME model was validated via the same process as the UTAUT model. The constructs PE, EE, and OR were found to have a positive, significant relationship with BI. Similar to findings during UTAUT validation, SI and FC were not strong predictors of BI.

After validation of each model, UTAUT and TAME were compared to determine which was a better fit for a manufacturing organization in a pre-implementation context. Results showed that TAME was more comprehensive in its prediction of BI as a measure of technology acceptance. The OR construct was a significant contributor to manufacturing employees' technology acceptance, which is an important finding supporting the need for a technology acceptance model with both individual and organizational constructs to adequately encompass the acceptance of manufacturing employees in a pre-implementation context.

Moderating variables were also explored in the relationship of each construct to BI. The variables of age, gender, and experience in manufacturing were determined to be possible moderators. For UTAUT, experience and gender slightly moderated PE ($p < 0.1$), but no moderating effects were found for EE. Analysis of TAME revealed that age, gender, and experience all moderate PE and OR, and gender and experience moderate EE.

In addition to statistical validation, differences in sub-groups were explored to determine whether there were varying levels of technology acceptance within the organization. Box plots and statistical difference analysis via Kruskal-Wallis and Mann-Whitney U tests were done by region, facility, department, job role, age, gender, and experience. Statistical differences were found for every variable but gender.

First, there was a gap in acceptance between the two regions where the study was conducted. Mexico had an overall higher level of technology acceptance than the United States. It is important to recognize that various cultural and demographical differences may affect technology acceptance levels in various regions of an organization. Once these are understood, the organization may make strategic adjustments to implement new technologies, such as launching in one region and then cross-deploying to another.

One of the more interesting findings was the difference between the Engineering department and others. Although technology acceptance levels were overall positive, the Engineering department had a lower level of technology acceptance than several other departments. This could be due to many reasons – some of which could be the role of the Engineering department at this particular organization – including a skepticism of the particular technology in question (in this case, AR), a hesitance to lead implementation efforts, or the lack of a clear business case for the organization. Regardless of the reason, the Engineering department is key to technology implementation in organizations. Research has shown that companies with more qualified engineers are more innovative, leading "to the development of a strong [advanced manufacturing technology] implementation culture" (Thomas et al., 2008). If engineers do not buy in, a successful implementation may be hindered.

Another interesting finding was the difference in acceptance between age groups. Millennials have a higher level of technology acceptance than Gen X or Boomers. As many employees of Gen X are not yet near retirement, it is crucial to ensure they accept the new technologies an organization wishes to implement. In the current research, responses from Gen X and Boomers were nearly double that of Millennials, matching overall demographic data from the organization. As the largest representation of the population, the Gen X and Boomer generations can greatly impact the success or failure of new technology. It is, therefore, important for organizations to ensure employees from all age groups are accepting of new technologies, and to focus on bolstering the acceptance levels of generations who may be more hesitant.

In summary, the major findings are:

- Objective 1: H_0 accepted. The pre-implementation UTAUT model is an adequate measure of technology acceptance levels of manufacturing employees in a pre-implementation context.
- Objective 2: $H_{1'}$ accepted. The TAME model is a more appropriate measure of technology acceptance levels of manufacturing employees in a pre-implementation context, with more variation of BI captured by the constructs.
    - Organizational readiness is a significant and key construct in predicting employee technology acceptance.
- Objective 3: $H_{1''}$ accepted. Differences in acceptance levels across regions, departments, and age groups should be considered in any technology implementation effort.
- Both individual and organizational constructs should be used in measuring employee technology acceptance.
- Performance and effort expectancy are significant constructs in predicting employee technology acceptance in both an individual acceptance model and a combined individual-organizational acceptance model.
- Human factors are an essential consideration in technology implementation efforts, and gauging employees' level of technology acceptance before a new technology launch can provide insight for organizations that may increase the chances of implementation success.

7.1 Limitations

No research effort is without limitations, and researchers need to identify where limitations exist to explain results in context. Limitations of this study are as follows:

- Participation was via self-selection, as the goal was to get as many responses as possible to ensure an adequate sample size for validity testing and to retain participant anonymity.
- Actual use was not measured, so criterion-related validity could not be established.
- The possible relationships between SI, FC, and actual use could also not be studied.
- The full-scale study was conducted with only one manufacturing organization; evaluating TAME in other manufacturing organizations will help extend the generalizability of this model.
- The full-scale study was conducted with only one type of technology, AR. Testing other technologies may produce different results.
- The English version of the survey had a video for participants to watch, and the Spanish version had photos as a reference. Although the same intent was maintained with the video and photos, using two different mediums could have led to differences in responding.

7.2 Future Research

While these studies suggest the viability of TAME in a pre-implementation manufacturing context, there are opportunities for future research related to this study. First, deploying this survey instrument with other population groups will continue to provide insight into the viability of the proposed model. TAME should be tested in other organizations within the manufacturing industry and with additional types of technology.

This study was unable to establish the criterion-related validity of either tested model. This limitation was inherent to the research design. Criterion-related validity requires quantitative results for comparison, and this study focused on the pre-implementation context. In the future, criterion-related validity may be established by measuring the use of any new technologies post-implementation and comparing model predictions with actual use data.

Measuring actual use will also allow for the study of possible relationships between SI and actual use and FC and actual use. Due to the intention to study a pre-implementation context, measuring actual use was outside the scope of this study. Therefore, the relationship between FC and actual use could not be derived from the current data. An analysis of FC with actual use data may lead to adding FC back to TAME as an antecedent of actual use but not BI (similar to the UTAUT model) or removing SI from the model if it has no relationship with actual use. Increasing FC may increase actual use after the technology is implemented but cannot be confirmed without further data collection.

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Appendices

Appendix A: UTAUT Instrument and Wording Changes for Pilot Phase

PE1
Original: I would find the system useful in my job.
Revised: I would find this technology useful in my job.

PE2
Original: Using the system enables me to accomplish tasks more quickly.
Revised: Using this technology would help me accomplish tasks more quickly.

PE3
Original: Using the system increases my productivity.
Revised: Using this technology would increase my productivity.

PE4
Original: If I use the system, I will increase my chances of getting a raise.
Revised: Using this technology would increase my chances of getting a raise, promotion, or other positive recognition.

EE1
Original: My interactions with the system would be clear and understandable.
Revised: My interactions with this technology would be clear and understandable.

EE2
Original: It would be easy for me to become skillful at using the system.
Revised: It would be easy for me to become skillful at using this technology.

EE3
Original: I would find the system easy to use.
Revised: This technology would be easy to use.

EE4
Original: Learning to operate the system is easy for me.
Revised: Learning to use this technology would be easy for me.

SI1

Original: People who influence my behavior think I should use the system.

Revised: My direct supervisor would want me to use this technology.

SI2
Original: People who are important to me think that I should use the system.
Revised: My peers would want me to use this technology.

SI3
Original: The senior management of this business has been helpful in the use of this system.
Revised: My senior manager or director would want me to use this technology.

SI4
Original: In general, the organization has supported the use of the system.
Revised: The organization as a whole would want me to use this technology.

FC1
Original: I have the resources necessary to use the system.
Revised: I have the resources necessary to use this technology.

FC2
Original: I have the knowledge necessary to use the system.
Revised: I have the knowledge/skills/abilities to use this technology.

FC3
Original: The system is not compatible with other systems I use.
Revised: This technology would be compatible with my other job tasks, equipment, and technologies I currently use.

FC4
Original: A specific person (or group) is available for assistance with system difficulties.
Revised: There is a specific person (or group) that could assist me with difficulties in using this technology.

BI1
Original: I intend to use the system in the next <n> months.
Revised: I am interested in using this technology.

BI2
Original: I predict I would use the system in the next <n> months.
Revised: I would actually use this technology in my current role.

Appendix B: Pilot Phase Survey Instrument

Demographic Information

1.	What is your gender? Male Female Other Prefer Not To Say
2.	What is your age? 18-24 25-29 30-39 40-49 50-59 60+
3.	What is your primary job responsibility? Front Line Leader/Supervisor Management Engineering Maintenance Other (please specify):________________
4.	How long have you worked in your current role? 0-3 months 4-6 months 7-11 months 1-3 years 4-6 years 6-10 years 10+ years
5.	How long have you worked in a manufacturing environment? 0-3 months 4-6 months 7-11 months 1-3 years 4-6 years 6-10 years 10+ years

Subject Matter Questionnaire

The following questions are about a technology called Google Glass. While this is a technology [redacted] may consider implementing in the future, the purpose of this survey is not to make a decision regarding adoption. Answers to the survey questions at this time will have no bearing on whether [redacted] plans to adopt Google Glass. The singular goal in surveying this specific technology is for statistical purposes to ensure everyone is answering questions about the same type of technology.

Google Glass is a pair of glasses designed to help the wearer do his or her job more efficiently. It is a physical pair of glasses that look like a standard pair of safety glasses. The glasses have a small rectangle on one side (similar to a bi-focal lens) that projects a small screen in front of the wearer's right eye. This visual display has a variety of capabilities, including step-by-step job instructions, picking sequences, repair troubleshooting, and remote communication connectivity. For example, a maintenance technician could call an equipment engineer in real time to troubleshoot concerns with an assist device, and the engineer would be able to see what the maintenance technician is seeing through the glasses. Alternately, a technician wearing the glasses could be shown a part picking sequence or SOS for a job.

With this information in mind, please answer the following questions using the scale below.

1	2	3	4	5
Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree

1. I would find Google Glass useful in my job.	1	2	3	4	5
2. Using Google Glass would help me accomplish tasks more quickly.	1	2	3	4	5
3. Using Google Glass would increase my productivity.	1	2	3	4	5
4. I would be open to trying Google Glass if my interaction with it was clear and understandable.	1	2	3	4	5
5. I would try Google Glass even if it were challenging to learn at first.	1	2	3	4	5
6. I think Google Glass would be easy to use with some training.	1	2	3	4	5
7. I think that my management would want me to use Google Glass.	1	2	3	4	5
8. I think that my peers would want me to use Google Glass.	1	2	3	4	5
9. My organization is committed to implementing new technologies.	1	2	3	4	5
10. My organization has the capability to implement Google Glass.	1	2	3	4	5
11. There is support for new technologies across all levels of my organization.	1	2	3	4	5
12. I would get the support I think I need to use Google Glass.	1	2	3	4	5
13. I have the knowledge/skills/abilities to use Google Glass.	1	2	3	4	5
14. Google Glass will be compatible with my other tasks.	1	2	3	4	5
15. I predict I would use Google Glass if given the opportunity.	1	2	3	4	5
16. I am interested in learning how to use Google Glass.	1	2	3	4	5

Appendix C: IRB Exempt Study Approval

Revised 08/23/2021

AUBURN UNIVERSITY HUMAN RESEARCH PROTECTION PROGRAM (HRPP)

EXEMPT REVIEW APPLICATION

For assistance, contact: **The Office of Research Compliance (ORC)**
Phone: **334-844-5966** E-Mail: **IRBAdmin@auburn.edu** Web Address: **http://www.auburn.edu/research/vpr/ohs**
Submit completed form and supporting materials as one PDF to IRBsumit@auburn.edu
Hand written forms are not accepted. Where links are found hold down the control button (Ctrl) then click the link..

1. Project Identification **Today's Date: November 22, 2021**

Anticipated start date of the project: November 1, 2021 Anticipated duration of project: 1 Year

a. Project Title: Technology Acceptance in the Manufacturing Environment

b. Principal Investigator (PI): Kristen Haynes Degree(s): MS
Rank/Title: Graduate Student Department/School: Industrial and Systems Engineering
Role/responsibilities in this project: **Experimental Design, Participant Recruitment, Consent Process, Data Collection/Interpretation/Analysis, Reporting Results**
Preferred Phone Number: **615-483-5616** AU Email: kmh0030@auburn.edu

Faculty Advisor Principal Investigator (if applicable): Gregory Harris
Rank/Title: Associate Professor Department/School: Industrial and Systems Engineering
Role/responsibilities in this project: **Oversight of Study Personnel, Experimental Design, Data Collection/Interpretation/Analysis, Reporting Results**
Preferred Phone Number: **334-844-1407** AU Email: greg.harris@auburn.edu

Department Head: John L. Evans Department/School: Industrial and Systems Engineering
Preferred Phone Number: **334.844.1418** AU Email: evansjl@auburn.edu
Role/responsibilities in this project: **Oversight of adherence to AU policies and procedures, federal/state/local laws, and ethical treatment of study participants**

c. Project Key Personnel – Identify all key personnel who will be involved with the conduct of the research and describe their role in the project. Role may include design, recruitment, consent process, data collection, data analysis, and reporting. (To determine key personnel, see decision tree**).** *Exempt determinations are made by individual institutions; reliance on other institutions for exempt determination is not feasible. Non-AU personnel conducting exempt research activities must obtain approval from the IRB at their home institution.*

Key personnel are required to maintain human subjects training through CITI. Only for EXEMPT level research is documentation of completed CITI training NO LONGER REQUIRED to be included in the submission packet. NOTE however, **the IRB will perform random audits of CITI training records to confirm** reported training courses and expiration dates. Course title and expiration dates are shown on training certificates.

Name: Click or tap here to enter text. Degree(s): Click or tap here to enter text.
Rank/Title: Choose Rank/Title Department/School: Choose Department/School
Role/responsibilities in this project: Click or tap here to enter text.
- AU affiliated? ☐ Yes ☐ No If no, name of home institution: Click or tap here to enter text.
- Do you have any known competing financial interests, personal relationships, or other interests that could have influence or appear to have influence on the work conducted in this project? ☐ Yes ☐ No
- If yes, briefly describe the potential or real conflict of interest: Click or tap here to enter text.
- Plan for IRB approval for non-AU affiliated personnel? Click or tap here to enter text.
- Completed required CITI training? ☐ Yes ☐ No If NO, complete the appropriate CITI basic course and update the revised Exempt Application form.
- If YES, choose course(s) the researcher has completed: Choose a course Expiration Date
Choose a course Expiration Date

The Auburn University Institutional Review Board has approved this Document for use from
___11/09/2021____to____-——_________
Protocol # ___21-528_______EX___2111____

Name: Click or tap here to enter text. Degree(s): Click or tap here to enter text.
Rank/Title: Choose Rank/Title Department/School: Choose Department/School
Role/responsibilities in this project: Click or tap here to enter text.
- AU affiliated? ☐ Yes ☐ No If no, name of home institution: Click or tap here to enter text.
- Do you have any known competing financial interests, personal relationships, or other interests that could have influence or appear to have influence on the work conducted in this project? ☐ Yes ☐ No
- If yes, briefly describe the potential or real conflict of interest: Click or tap here to enter text.
- Plan for IRB approval for non-AU affiliated personnel? Click or tap here to enter text.
- Completed required CITI training? ☐ Yes ☐ No If NO, complete the appropriate CITI basic course and update the revised EXEMPT application form.
- If YES, choose course(s) the researcher has completed: Choose a course Expiration Date
Choose a course Expiration Date

Name: Click or tap here to enter text. Degree(s): Click or tap here to enter text.
Rank/Title: Choose Rank/Title Department/School: Choose Department/School
Role/responsibilities in this project: Click or tap here to enter text.
- AU affiliated? ☐ Yes ☐ No If no, name of home institution: Click or tap here to enter text.
- Do you have any known competing financial interests, personal relationships, or other interests that could have influence or appear to have influence on the work conducted in this project? ☐ Yes ☐ No
- If yes, briefly describe the potential or real conflict of interest: Click or tap here to enter text.
- Plan for IRB approval for non-AU affiliated personnel? Click or tap here to enter text.
- Completed required CITI training? ☐ Yes ☐ No If NO, complete the appropriate CITI basic course and update the revised EXEMPT application form.
- If YES, choose course(s) the researcher has completed: Choose a course Expiration Date
Choose a course Expiration Date

a. Funding Source – Is this project funded by the investigator(s)? Yes ☐ No ☒
Is this project funded by AU? Yes ☐ No ☒ If YES, identify source N/A
Is this project funded by an external sponsor? Yes ☐ No ☒ If YES, provide name of sponsor, type of sponsor (governmental, non-profit, corporate, other), and an identification number for the award.
Name: **N/A** Type: **N/A** Grant #: **N/A**

b. List other AU IRB-approved research projects and/or IRB approvals from other institutions that are associated with this project. Describe the association between this project and the listed project(s):
N/A

2. Project Summary

a. Does the study *TARGET* any special populations? Answer YES or NO to all.

Minors (under 18 years of age)	Yes ☐	No ☒
Auburn University Students	Yes ☐	No ☒
Pregnant women, fetuses, or any products of conception	Yes ☐	No ☒
Prisoners or wards (unless incidental, not allowed for Exempt research)	Yes ☐	No ☒
Temporarily or permanently impaired	Yes ☐	No ☒

Revised 08/23/2021

a. Does the research pose more than minimal risk to participants? Yes ☐ No ☒

If YES, to question 2.b, then the research activity is NOT eligible for EXEMPT review.

Minimal risk means that the probability and magnitude of harm or discomfort anticipated in the research is not greater in and of themselves than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or test. 42 CFR 46.102(i)

b. Does the study involve any of the following? *If YES to any of the questions in item 2.c, then the research activity is NOT eligible for EXEMPT review.*

Procedures subject to FDA regulations (drugs, devices, etc.) Yes ☐ No ☒

Use of school records of identifiable students or information from instructors about specific students. Yes ☐ No ☒

Protected health or medical information when there is a direct or indirect link which could identify the participant. Yes ☐ No ☒

Collection of sensitive aspects of the participant's own behavior, such as illegal conduct, drug use, sexual behavior or alcohol use. Yes ☐ No ☒

c. Does the study include deception? Requires limited review by the IRB* Yes ☐ No ☒

2. MARK the category or categories below that describe the proposed research. Note the IRB Reviewer will make the final determination of the eligible category or categories.

☐ **1.** Research conducted in established or commonly accepted educational settings, involving normal educational practices. The research is not likely to adversely impact students' opportunity to learn or assessment of educators providing instruction. 104(d)(1)

☒ **2.** Research only includes interactions involving educational tests, surveys, interviews, public observation if at least ONE of the following criteria. (The research includes data collection only; may include visual or auditory recording; may NOT include intervention and only includes interactions). **Mark the applicable sub-category below (I, ii, or iii). 104(d)(2)**

☒ **(i)** Recorded information cannot readily identify the participant (directly or indirectly/ linked);
OR
- surveys and interviews: no children;
- educational tests or observation of public behavior: can only include children when investigators do not participate in activities being observed.

☐ **(ii)** Any disclosures of responses outside would not reasonably place participant at risk; **OR**

☐ **(iii)** Information is recorded with identifiers or code linked to identifiers and IRB conducts limited review; no children. **Requires limited review by the IRB.***

3. Research involving Benign Behavioral Interventions (BBI)** through verbal, written responses including data entry or audiovisual recording from adult subjects who prospectively agree and ONE of the following criteria is met. (This research does not include children and does not include medical interventions. Research cannot have deception unless the participant prospectively agrees that they will be unaware of or misled regarding the nature and purpose of the research) **Mark the applicable sub-category below (A, B, or C).**

☐ **(A)** Recorded information cannot readily identify the subject (directly or indirectly/ linked); **OR**

☐ **(B)** Any disclosure of responses outside of the research would not reasonably place subject at risk; **OR**

☐ **(C)** Information is recorded with identifies and cannot have deception unless participants prospectively agrees. **Requires limited review by the IRB.***

☐ **4.** Secondary research for which consent is not required: use of identifiable information or identifiable bio-specimen that have been or will be collected for some other 'primary' or 'initial' activity, if one of the following criteria is met. Allows retrospective and prospective secondary use. **Mark the applicable sub-category below (i, ii, iii, or iv).** 104 (d)(4)

☐ **(i)** Bio-specimens or information are publicly available;

☐ **(ii)** Information recorded so subject cannot readily be identified, directly or indirectly/linked investigator does not contact subjects and will not re-identify the subjects; **OR**

☐ **(iii)** Collection and analysis involving investigators use of identifiable health information when us is regulated by HIPAA "health care operations" or "research" or "public health activities and purposes" (does not include bio-specimens (only PHI and requires federal guidance on how to apply); **OR**

☐ **(iv)** Research information collected by or on behalf of federal government using government generated or collected information obtained for non-research activities.

☐ **5.** Research and demonstration projects which are supported by a federal agency/department AND designed to study and which are designed to study, evaluate, or otherwise examine: (i)public benefit or service programs; (ii) procedures for obtaining benefits or services under those programs; (iii) possible changes in or alternatives to those programs or procedures; or (iv) possible changes in methods or levels of payment for benefits or service under those programs. (must be posted on a federal web site). 104.5(d)(5) (must be posted on a federal web site)

☐ **6.** Taste and food quality evaluation and consumer acceptance studies, (i) if wholesome foods without additives and consumed or (ii) if a food is consumed that contains a food ingredient at or below the level and for a use found to be safe, or agricultural chemical or environmental contaminant at or below the level found to be safe, by the Food and Drug Administration or approved by the Environmental Protection Agency or the Food Safety and Inspection Service of the U.S. Department of Agriculture. The research does not involve prisoners as participants. 104(d)(6)

***Limited IRB review – the IRB Chair or designated IRB reviewer reviews the protocol to ensure adequate provisions are in place to protect privacy and confidentiality.*

***Category 3 – Benign Behavioral Interventions (BBI) must be brief in duration, painless/harmless, not physically invasive, not likely to have a significant adverse lasting impact on participants, and it is unlikely participants will find the interventions offensive or embarrassing.*

Revised 08/23/2021

**** Exemption categories 7 and 8 require broad consent. The AU IRB has determined the regulatory requirements for legally effective broad consent are not feasible within the current institutional infrastructure. EXEMPT categories 7 and 8 will not be implemented at this time.*

1. Describe the proposed research including who does what, when, where, how, and for how long, etc.

a. Purpose

Provide framework to help OEMs identify gaps hindering successful technology implementation

b. Participant population, including the number of participants and the rationale for determining the number of participants to recruit and enroll.

Participants will be at least 200 adults over the age of 18 currently employed by a large automotive manufacturer. This number is based on statistically significant sample size needs of previous similar research.

In addition to enrollment in Auburn's PhD program, the student PI is employed with [redacted] full time as a Manufacturing Engineer. Responsibilities include engineering project management and strategic planning.

c. Recruitment process. Address whether recruitment includes communications/interactions between study staff and potential participants either in person or online. *Submit a copy of all recruitment materials.*

An electronic survey will be made available through a company app to approximately 10,000 employees currently working at a large automotive manufacturer. Participants will be recruited through the PI's employer, who will advertise the survey in a weekly company newsletter. Participants will click a link through an existing app used for company communications that will take them to an informational letter about the study. The letter will include a study description and indication that participation is completely voluntary with no identifiable information collected. After reading and agreeing, they will be taken to the survey.

d. Consent process including how information is presented to participants, etc.

Access to the survey will be through a company app used for employee communication and engagement. A short recruitment announcement will be made via company newsletter, where employees will be informed to access the survey via the app. Once employees click the survey access link in the app, they will be presented with an electronic informational letter about the study and what they can expect. The letter will inform participants that by clicking through to proceed to the survey, they will be giving consent. After clicking to proceed, participants will be taken to Survey Monkey to anonymously complete the survey.

e. Research procedures and methodology

An electronic survey will be made available through a company app to approximately 10,000 [redacted] employees over the age of 18 currently working in a vehicle manufacturing plant. Participants will click a link through an existing app used for company communications that will take them to an informational letter about the study. The letter will include a study description and indication that participation is completely voluntary with no identifiable information collected.

In addition to basic demographic questions, participants will be asked to answer 16 questions in 6 different categories. All questions are related to how participants feel about the potential adoption of a technology called Google Glass, which is a pair of glasses designed to help the wearer do his or her job more efficiently. This technology includes a visual display and voice communication capabilities. Some of the uses for Google Glass are step-by-step job instructions, picking sequence, repair troubleshooting, and remote communication connectivity (for example, engineering to production floor). Prior to beginning the survey, participants will receive a short description of the technology similar to the above as a reference for answering questions.

The first category includes 3 questions related to performance expectancy, or whether participants feel that Google Glass would help make their job easier. The next 3 questions are about performance expectancy, or how easy participants feel Google Glass would be to use. The next 2 questions are related to social influence, or the pressure participants feel from management and/or peers to use the technology. The following 3 questions are related to organizational readiness, or the level to which a participant feels the organization is prepared to implement Google Glass. The next construct consists of 3 questions related to facilitating conditions, or the participants' belief in the level of organizational support he/she will receive in implementing Google Glass. The last 2 questions are related to behavioral intention, or participants' intention to use and learn Google Glass. All questions will be rated on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

The online survey tool Survey Monkey will be used to create and deliver the survey, and to collect data. The survey will be distributed between the dates of November 15, 2021 and May 31, 2022. Participants will complete the survey via an app on a personal electronic device. The data collected will be used to determine levels of acceptance for implementing a new technology in the workplace. This information will then be used to determine statistically significant parameters to consider when implementing new technology in a manufacturing environment. A model will also be created from the results.

a. Anticipated time per study exercise/activity and total time if participants complete all study activities.
Approximately 10-15 minutes

b. Location of the research activities.
Electronic, no specified location

c. Costs to and compensation for participants? If participants will be compensated describe the amount, type, and process to distribute.
There will be no costs or compensation for participants.

d. Non-AU locations, site, institutions. *Submit a copy of agreements/IRB approvals.*
[redacted]

e. Additional relevant information.
Click or tap here to enter text.

2. Waivers
Check applicable waivers and describe how the project meets the criteria for the waiver.

☐ Waiver of Consent (Including existing de-identified data)

☒ Waiver of Documentation of Consent (Use of Recruitment/Information Letter, rather than consent form requiring signatures)

☐ Waiver of Parental Permission (in Alabama, 18 years-olds may be considered adults for research purposes)

a. Provide the rationale for the waiver request.
All study procedures occur online and there is no mechanism for obtaining participants' signatures on a consent form.

3. Describe the process to select participants/data/specimens. If applicable, include gender, race, and ethnicity of the participant population.

Participants who are adults over 18 years of age and employed by [redacted] will be eligible for participation. There will be no exclusions based on gender, race, ethnicity, or other parameters.

1. **Describe why none of the research procedures would cause a participant either physical or psychological discomfort or be perceived as discomfort above and beyond what the person would experience in daily life (minimal risk).**

Participation in this study involves taking a survey about the possibility of bringing new technologies to the workplace. There is no physical requirement for participation. Participants may experience some psychological discomfort when considering how new technology adoption may affect their job, but not beyond what they experience daily at the workplace. When considering new technology, the main concern is typically threat to job security. However, the technology described in the survey (Google Glass) is intended to aid employees in job efficiency and not likely to be perceived as a technology that may threaten employees' job security in any way.

2. **Describe the provisions to maintain confidentiality of data, including collection, transmission, and storage. Identify platforms used to collect and store study data.** *For EXEMPT research, the AU IRB recommends AU BOX or using an AU issued and encrypted device. If a data collection form will be used, submit a copy.*

The electronic survey data will be collected through an app via an anonymous survey link with no traceable identifying information. The survey will be conducted through the online survey creation and distribution software Survey Monkey. The data will be stored in AU BOX.

   a. If applicable, submit a copy of the data management plan or data use agreement.

NDA signed by all necessary parties

3. **Describe the provisions included in the research to protect the privacy interests of participants (e.g., others will not overhear conversations with potential participants, individuals will not be publicly identified or embarrassed).**

Participants will take the survey via an app downloaded on a personal electronic device, so they will be able to choose when and where they prefer to take the survey.

4. **Additional Information and/or attachments.**
In the space below, provide any additional information you believe may help the IRB review of the proposed research. If attachments are included, list the attachments below. Attachments may include recruitment materials, consent documents, site permissions, IRB approvals from other institutions, data use agreements, data collection form, CITI training documentation, etc.

Study materials: recruitment/information letter, NDA, [redacted] letter of support, survey

Revised 08/23/2021

Required Signatures *(If a student PI is identified in item 1.a, the EXEMPT application <u>must</u> be re-signed and updated at <u>every</u> revision by the student PI and faculty advisor. The signature of the department head is required <u>only</u> on the initial submission of the EXEMPT application, regardless of PI. Staff and faculty PI submissions require the PI signature on all version, the department head signature on the original submission)*

Signature of Principal Investigator: Kristen Haynes **Date:** 11/22/21

Signature of Faculty Advisor (If applicable): **Date:_Nov. 18, 2021**

Signature of Dept. Head: **Date:_ Nov. 18, 2021**

Version Date: 11/22/2021

Appendix D: TAME Survey Instrument (English Version)

Demographic Information

6. What is your gender? Male Female Non-Binary Self-Describe ________________________________
7. What is your age? 18-24 25-34 35-44 45-54 55-64 65+
8. At which site do you work? [*redacted*]
9. Where in the facility do you work? Stamping Body Paint Trim/Chassis PQA Engineering Maintenance SCM Other ______________
10. What is your job title?
11. How long have you worked in your current role?
12. How long have you worked in a manufacturing environment?

Subject Matter Questionnaire

The goal of this survey is to find out employees' opinions on using augmented reality (AR) technology. AR is an interactive technology that shows a user virtual images in real-world scenarios. Some examples of AR uses in manufacturing are broadcast display, parts picking sequence, step-by-step job instruction display, and interactive repair troubleshooting. While the organization may consider using this technology in the future, answers to the survey questions at this time will not affect plans to adopt this technology or not.

Please watch the short video below (~2 min) to familiarize yourself with an example of this technology, and then answer the following questions accordingly.

https://youtu.be/Fwikx1TOidE

Questionnaire

1	2	3	4	5	6	7
Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree

1. I would find this technology useful in my job.	1	2	3	4	5	6	7
2. Using this technology would help me accomplish tasks more quickly.	1	2	3	4	5	6	7
3. Using this technology would increase my productivity.	1	2	3	4	5	6	7
4. Using this technology would increase my chances of getting a raise, promotion, or other positive recognition.	1	2	3	4	5	6	7
5. My interactions with this technology would be clear and understandable.	1	2	3	4	5	6	7
6. It would be easy for me to become skillful at using this technology.	1	2	3	4	5	6	7
7. This technology would be easy to use.	1	2	3	4	5	6	7
8. Learning to use this technology would be easy for me.	1	2	3	4	5	6	7
9. My direct supervisor would want me to use this technology.	1	2	3	4	5	6	7
10. My peers would want me to use this technology.	1	2	3	4	5	6	7
11. My senior manager or director would want me to use this technology.	1	2	3	4	5	6	7
12. The organization as a whole would want me to use this technology.	1	2	3	4	5	6	7
13. I have the resources necessary to use this technology.	1	2	3	4	5	6	7
14. I have the knowledge/skills/abilities to use this technology.	1	2	3	4	5	6	7
15. This technology would be compatible with my other job tasks, equipment, and technologies I currently use.	1	2	3	4	5	6	7
16. There is a specific person (or group) that could assist me with difficulties in using this technology.	1	2	3	4	5	6	7
17. I am interested in using this technology.	1	2	3	4	5	6	7
18. I would actually use this technology in my current role.	1	2	3	4	5	6	7
19. I am interested in learning how to use this technology.	1	2	3	4	5	6	7
20. I would try this technology even if it were challenging to learn at first.	1	2	3	4	5	6	7

Appendix E: IRB Modification 1 Approval

AUBURN UNIVERSITY HUMAN RESEARCH PROTECTION PROGRAM (HRPP)

REQUEST for MODIFICATION

For Information or help completing this form, contact: **The Office of Research Compliance (ORC)**
Phone: **334-844-5966** E-Mail: **IRBAdmin@auburn.edu**

- **Federal regulations require IRB approval before implementing proposed changes.**
- **Change means any change, in content or form, to the protocol, consent form, or any supportive materials (such as the investigator's Brochure, questionnaires, surveys, advertisements, etc.). See Item 4 for more examples.**

1. Today's Date	3/21/2022

2. Principal Investigator (PI) Name: Kristen Haynes			
PI's Title:	Graduate Student	**Faculty PI (if PI is a student):**	Gregory Harris
Department:	Industrial and Systems Engineering	**Department:**	Industrial and Systems Engineering
Phone:	6154835616	**Phone:**	3348441407
AU-E-Mail:	Kmh0030@auburn.edu	**AU E-Mail:**	Greg.harris@auburn.edu
Contact person who should receive copies of IRB correspondence (Optional):	Click or tap here to enter text.	**Department Head Name:**	John Evans
Phone:	Click or tap here to enter text.	**Phone:**	3348441418
AU E-Mail:	Click or tap here to enter text.	**AU E-Mail:**	evansjl@auburn.edu

3. AU IRB Protocol Identification	
3.a. Protocol Number: 21-528	
3.b. Protocol Title: Technology Acceptance in the Manufacturing Environment	
3. c. Current Status of Protocol – For active studies, check ONE box at left; provide numbers and dates where applicable	
☐ **Study has not yet begun; no data has been entered or collected**	
☒ **In progress If YES, number of data/participants entered: 26** ☐ **Is this modification request being made in conjunction with/as a result of protocol renewal?** ☐ **YES** ☒ **NO** ☐ **Adverse events since last review If YES, describe:** Click or tap here to enter text. ☐ **Data analysis only**	**Current Approval Dates** **From: 11/9/2021** **To: 11/9/2022**
☐ **Funding Agency and Grant Number:** Click or tap here to enter text.	**AU Funding Information:** Click or tap here to enter text.
☐ **List any other institutions and/ or AU approved studies associated with this project:** Click or tap here to enter text.	

The Auburn University Institutional
Review Board has approved this
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__03/21/2022___to____-______________
Protocol # ___21-528_______EX___2111____

Page 1

4. Types of Change	
	Mark all that apply, and describe the changes in item 5
☐	**Change in Key Personnel** Attach CITI forms to add new personnel.
☐	**Additional Sites or Change in Sites, including AU classrooms, etc.** Attach permission forms for new sites.
☐	**Change in methods for data storage/ protection or location of data/ consent documents**
☒	**Change in project purpose or project questions**
☒	**Change in population or recruitment** Attach new or revised recruitment materials as needed; both highlighted version & clean copy for IRB approval stamp
☒	**Change in study procedure(s)** Attach new or revised consent documents as needed; both highlighted revised copy & clean copy for IRB approval stamp
☒	**Change in data collection instruments/forms (surveys, data collection forms)** Attach new forms as needed; both highlighted version & clean copy for IRB approval stamp
☐	**Other** (BUAs, DUAs, etc.) Indicate the type of change in the space below, and provide details in the Item 5.c. or 5.d. as applicable. Include a copy of all affected documents, with revisions highlighted as applicable. Click or tap here to enter text.

5. Description and Rationale
5.a. For each item marked in Question #4 describe the requested change(s) to your research protocol, and the rationale for each.
Survey changes: oRewording of demographic questions and answer formatting oAdditional survey questions based on first pilot study feedback oAddition of video in technology description section Provision for additional participant recruitment measures Provision for additional survey dissemination method (paper)
5.b. Briefly list (numbered or bulleted) **the activities that have occurred up to this point, particularly those that involved participants.**
Preliminary pilot study conducted with AU students only
5.c. Does the requested change affect participants, such as procedures, risks, costs, benefits, etc.
No
5.d. Attach a copy of all "IRB stamped" documents currently used. (Information letters, consent forms, flyers, etc.)
Click or tap here to enter text.
5.e. Attach a copy of all revised documents (high-lighted revised version and clean revised version for the IRB approval stamp).
Click or tap here to enter text.

6. Signatures
Principal Investigator Kristen Haynes ______
Faculty Advisor PI, if applicable Gregory A. Harris ______

Version Date: 3/21/2022

Appendix F: Recruitment and Information Letter

RECRUITMENT DOCUMENT & INFORMATION LETTER
For a Research Study entitled
"Employee Perception of Technology Readiness in a Manufacturing Organization"

You are invited to participate in a research study to evaluate key components of technology acceptance in a manufacturing environment.

This study is being conducted by [*redacted*] through a partnership with Auburn University aimed at studying new technology adoption in manufacturing. This particular survey is being conducted by Kristen Haynes, [*redacted*] manufacturing engineer and Auburn graduate student. You were selected as a possible participant because [*redacted*] is interested in your opinion on new technology implementation in the workplace.

Your participation is completely voluntary. If you decide to participate in this research study, you will be asked to complete a short survey about your perspective on technology adoption in a manufacturing environment. Your total time commitment will be approximately 10-15 minutes. You may answer all of the questions, some of the questions or none of the questions.

No data identifying you will be collected directly or indirectly. No IP address will be recorded, and all your responses will be kept strictly confidential. You may complete this study during work time. You will have no costs associated with completing this survey. You will receive no additional compensation or direct benefit, and no risks are anticipated from participation.

If you have questions about this study, please contact Kristen Haynes at [*redacted*] or Dr. Gregory Harris, Ph.D., P.E. at greg.harris@auburn.edu.

By proceeding you consent to participate in this survey.

Best,
Kristen Haynes
Manufacturing Engineer | [*redacted*]
Ph.D. Candidate | Auburn University | Industrial and Systems Engineering |
Kmh0030@auburn.edu

The Auburn University Institutional Review Board has approved this document for use from

11/9/21 to --------- Protocol #21-528 EX 2111.

Appendix G: TAME Survey Instrument (Spanish Version)

DOCUMENTO PARA RECLUTAMENTO Y CARTA DE INFORMACIÓN
Para un Proyecto de Investigación titulado
"Percepción del Empleado en la Preparación Tecnológica en una Organización de Manufactura"

Has sido invitado a participar en un proyecto de investigación para evaluar los principales elementos en la apertura hacia nuevas tecnologías en el ambiente de manufactura.

Este estudio está siendo conducido por [*redacted*] en colaboración con la Universidad de Auburn en los Estados Unidos, y tiene como objetivo el estudiar la adopción de nuevas tecnologías en manufactura. La encuesta en particular está siendo conducida por Kristen Haynes, ingeniero de manufactura en [*redacted*] y estudiante de la escuela de graduados de Auburn. Tú has sido elegido como posible participante porque [*redacted*] está interesado en tú opinión sobre la implementación de nuevas tecnologías en el piso de trabajo.

Tú participación es completamente voluntaria. Si decides participar en el proyecto de investigación se solicitará llenar una breve encuesta acerca de tu perspectiva en la adopción de nuevas tecnologías en el ambiente de manufactura.
El tiempo total requerido para la encuesta es de aproximadamente 10 a 15 minutos. Puedes responder a todas las preguntas, a algunas de ellas, o a ninguna.

Ningún dato que te identifique será recolectado de manera directa o indirecta. No se grabará tu dirección IP, y todas tus respuestas se mantendrán de manera confidencial. Puedes completar este proyecto durante tu horario de trabajo. No habrá costo asociado al llenado de la encuesta. Tampoco recibirás compensación o beneficio directo, y no se ha anticipado riesgo alguno por la participación en el proyecto.

Si tienes preguntas acerca del proyecto, favor de contactar a Kristen Haynes al correo electrónico Kristen.haynes@[*redacted*] o al Dr. Gregory Harris, Ph.D., P.E. al correo electrónico greg.harris@auburn.edu.

Al proceder estas dando tu consentimiento para participar en esta encuesta.

Saludos,
Kristen Haynes
Ingeniero de Manufactura | [*redacted*]
Candidata a Doctorado | Universidad de Auburn | Ingeniería Industrial y en Sistemas |
Kmh0030@auburn.edu

El Panel de Revisión Institucional de la Universidad de Auburn ha aprobado este documento para su uso a partir del 9 de Noviembre del 2021 al ---------
Protocolo #21-520 EX 211.

Percepción del Empleado en la Preparación Tecnológica en una Organización de Manufactura

Información Demográfica

13. ¿Cuál es tu género? Hombre Mujer No Binario Descríbete ______________________
14. ¿Cuál es tu edad? 18-24 25-34 35-44 45-54 55-64 65+
15. ¿En qué planta laboras? [*redacted*]
16. ¿En qué área de la planta trabajas? Estampado Carrocerías Pintura Vestiduras Calidad Ingeniería Mantenimiento Logística Otro __________
17. ¿Cuál es el nombre de tu puesto de trabajo?
18. ¿Por cuánto tiempo has trabajado en tu actual puesto?
19. ¿Por cuánto tiempo has laborado en el sector de manufactura?

Encuesta sobre el Tema

El objetivo de esta encuesta es recolectar la opinión del empleado acerca del uso de la tecnología de realidad aumentada (RA). RA es una tecnología interactiva que permite a los usuarios ver imágenes virtuales en escenarios del mundo real. Algunos ejemplos de cómo se utiliza RA en manufactura son despliegue de información, secuencia en la selección de partes (parts picking), despliegue paso a paso de las instrucciones de trabajo, y ayuda interactiva cuando se realizan actividades de mantenimiento o reparaciones. Aunque la organización podría considerar la implementación de dicha tecnología en el futuro, por el momento las respuestas a este cuestionario no tendrán peso en sobre si la organización planea adoptar esta tecnología.

Favor de ver el breve video que viene en la liga de abajo (~2 min) para que te familiarices con un ejemplo de dicha tecnología, y después puedas contestar la encuesta sobre el tema.

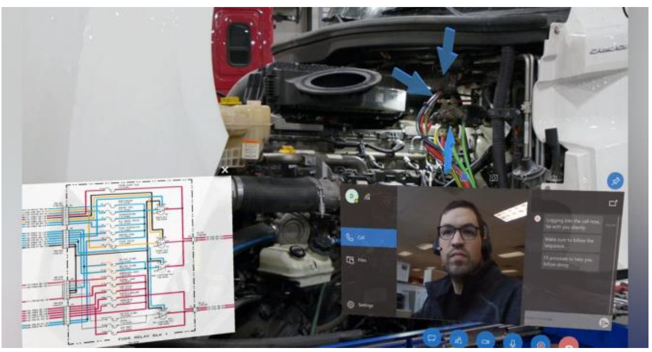
https://youtu.be/Fwikx1TOidE

Si participas en la encuesta en papel o no puedes accesar el video, favor de revisar las fotografías mostradas abajo para ver ejemplos de realidad aumentada, y contesta a las preguntas que se encuentran a continuación.

https://images.app.goo.gl/Tcpg6pHkZ5LgbVGi9
Instrucciones de Trabajo

https://images.app.goo.gl/AyKWAzUUF37zYgN6A
Secuencia en la toma de piezas

https://images.app.goo.gl/A2TiWEeXHB3T5YNo6
Inspecciones



https://images.app.goo.gl/ve5rAWeakSErgxtu5
Entrenamiento en el lugar de trabajo y apoyo remoto

Cuestionario

1	2	3	4	5	6	7
Totalmente en desacuerdo	En desacuerdo	Algo en desacuerdo	Ni de acuerdo ni en desacuerdo	Algo de acuerdo	De acuerdo	Totalmente de acuerdo

1. Encuentro esta tecnología útil para mi trabajo.	1	2	3	4	5	6	7
2. El uso de esta tecnología me ayudaría a completar mi trabajo de forma más rápida.	1	2	3	4	5	6	7
3. El uso de esta tecnología me haría más productive.	1	2	3	4	5	6	7
4. El uso de esta tecnología incrementaría mis oportunidades de lograr un aumento, promoción, u otro reconocimiento favorable.	1	2	3	4	5	6	7
5. La forma de interactuar con esta tecnología sería clara y entendible.	1	2	3	4	5	6	7
6. Sería fácil para mi llegar a ser hábil usando esta tecnología.	1	2	3	4	5	6	7
7. Esta tecnología sería fácil de usar.	1	2	3	4	5	6	7
8. Aprender a usar esta tecnología sería fácil para mí.	1	2	3	4	5	6	7
9. A mi supervisor directo le interesaría que yo usara esta tecnología.	1	2	3	4	5	6	7
10. A mis compañeros les interesaría que yo usara esta tecnología.	1	2	3	4	5	6	7
11. A mi gerente o director le interesaría que yo usara esta tecnología.	1	2	3	4	5	6	7
12. A la organización en general le interesaría que yo usara esta tecnología.	1	2	3	4	5	6	7
13. Tengo los recursos necesarios para utilizar este tecnología.	1	2	3	4	5	6	7
14. Tengo los conocimientos/competencias/habilidades para utilizar esta tecnología.	1	2	3	4	5	6	7
15. Esta tecnología sería compatible con mis otras actividades, equipo y tecnologías que actualmente uso.	1	2	3	4	5	6	7
16. Hay una persona (o grupo) específico que podría apoyarme con las dificultades en el uso de esta tecnología.	1	2	3	4	5	6	7
17. Estoy interesado en usar esta tecnología.	1	2	3	4	5	6	7
18. Estaría usando actualmente esta tecnología en mi puesto actual.	1	2	3	4	5	6	7
19. Estoy interesado en aprender cómo usar esta tecnología.	1	2	3	4	5	6	7
20. Probaría esta tecnología aún y cuando fuera complicado aprenderla en un principio.	1	2	3	4	5	6	7

21. Mi organización está comprometida en implementar nuevas tecnologías.	1	2	3	4	5	6	7
22. Mi organización tiene los recursos para apoyar la implementación de nuevas tecnologías.	1	2	3	4	5	6	7
23. Mi organización tiene un historial de apoyar la implementación de nuevas tecnologías.	1	2	3	4	5	6	7
24. Mi organización se beneficiaría con la implementación de nuevas tecnologías.	1	2	3	4	5	6	7

Appendix H: IRB Modification 2 Approval

AUBURN UNIVERSITY HUMAN RESEARCH PROTECTION PROGRAM (HRPP)

REQUEST for MODIFICATION

For Information or help completing this form, contact: **The Office of Research Compliance (ORC)**
Phone: **334-844-5966** E-Mail: **IRBAdmin@auburn.edu**

- **Federal regulations require IRB approval before implementing proposed changes.**
- **Change means any change, in content or form, to the protocol, consent form, or any supportive materials (such as the investigator's Brochure, questionnaires, surveys, advertisements, etc.). See Item 4 for more examples.**

1. Today's Date	6/12/2022

2. Principal Investigator (PI) Name: Kristen Haynes			
PI's Title:	Graduate Student	**Faculty PI (if PI is a student):**	Gregory Harris
Department:	Industrial and Systems Engineering	**Department:**	Industrial and Systems Engineering
Phone:	6154835616	**Phone:**	3348441407
AU-E-Mail:	Kmh0030@auburn.edu	**AU E-Mail:**	Greg.harris@auburn.edu
Contact person who should receive copies of IRB correspondence (Optional):	Click or tap here to enter text.	**Department Head Name:**	Click or tap here to enter text.
Phone:	Click or tap here to enter text.	**Phone:**	Click or tap here to enter text.
AU E-Mail:	Click or tap here to enter text.	**AU E-Mail:**	Click or tap here to enter text.

3. AU IRB Protocol Identification	
3.a. Protocol Number: 21-528	
3.b. Protocol Title: Employee Perception of Technology Readiness in a Manufacturing Organization	
3. c. Current Status of Protocol – For active studies, check ONE box at left; provide numbers and dates where applicable	
☐ **Study has not yet begun; no data has been entered or collected**	
☒ **In progress** **If YES, number of data/participants entered:** 664 ☐ **Is this modification request being made in conjunction with/as a result of protocol renewal?** ☐ **YES** ☒ **NO** ☐ **Adverse events since last review** **If YES, describe:** Click or tap here to enter text. ☐ **Data analysis only**	**Current Approval Dates** **From: 11/9/2021** **To: 11/9/2022**
☐ **Funding Agency and Grant Number:** Click or tap here to enter text.	**AU Funding Information:** Click or tap here to enter text.
☐ **List any other institutions and/ or AU approved studies associated with this project:** Click or tap here to enter text.	

The Auburn University Institutional Review Board has approved this Document for use from
___06/14/2022__to___-________________
Protocol # ___21-528_______EX__2111____

Page 1

4. Types of Change Mark all that apply, and describe the changes in item 5	
☐	**Change in Key Personnel** Attach CITI forms to add new personnel.
☒	**Additional Sites or Change in Sites, including AU classrooms, etc.** Attach permission forms for new sites.
☐	**Change in methods for data storage/ protection or location of data/ consent documents**
☐	**Change in project purpose or project questions**
☒	**Change in population or recruitment** Attach new or revised recruitment materials as needed; both highlighted version & clean copy for IRB approval stamp
☐	**Change in study procedure(s)** Attach new or revised consent documents as needed; both highlighted revised copy & clean copy for IRB approval stamp
☒	**Change in data collection instruments/forms (surveys, data collection forms)** Attach new forms as needed; both highlighted version & clean copy for IRB approval stamp
☐	**Other** (BUAs, DUAs, etc.) Indicate the type of change in the space below, and provide details in the Item 5.c. or 5.d. as applicable. Include a copy of all affected documents, with revisions highlighted as applicable. Click or tap here to enter text.

5. Description and Rationale
5.a. For each item marked in Question #4 describe the requested change(s) to your research protocol, and the rationale for each.
- Population extension: employees at [redacted] Mexico production facilities - expanding scope of study - Direct translation of survey and recruitment materials to Spanish for employees in Mexico - better understanding for native Spanish speakers - Addition of photo examples to questionnaire - for paper survey dissemination
5.b. Briefly list (numbered or bulleted) **the activities that have occurred up to this point, particularly those that involved participants.**
Preliminary pilot study completed, study 1 complete
5.c. Does the requested change affect participants, such as procedures, risks, costs, benefits, etc.
No
5.d. Attach a copy of all "IRB stamped" documents currently used. (Information letters, consent forms, flyers, etc.)
Click or tap here to enter text.
5.e. Attach a copy of all revised documents (high-lighted revised version and clean revised version for the IRB approval stamp).
Click or tap here to enter text.

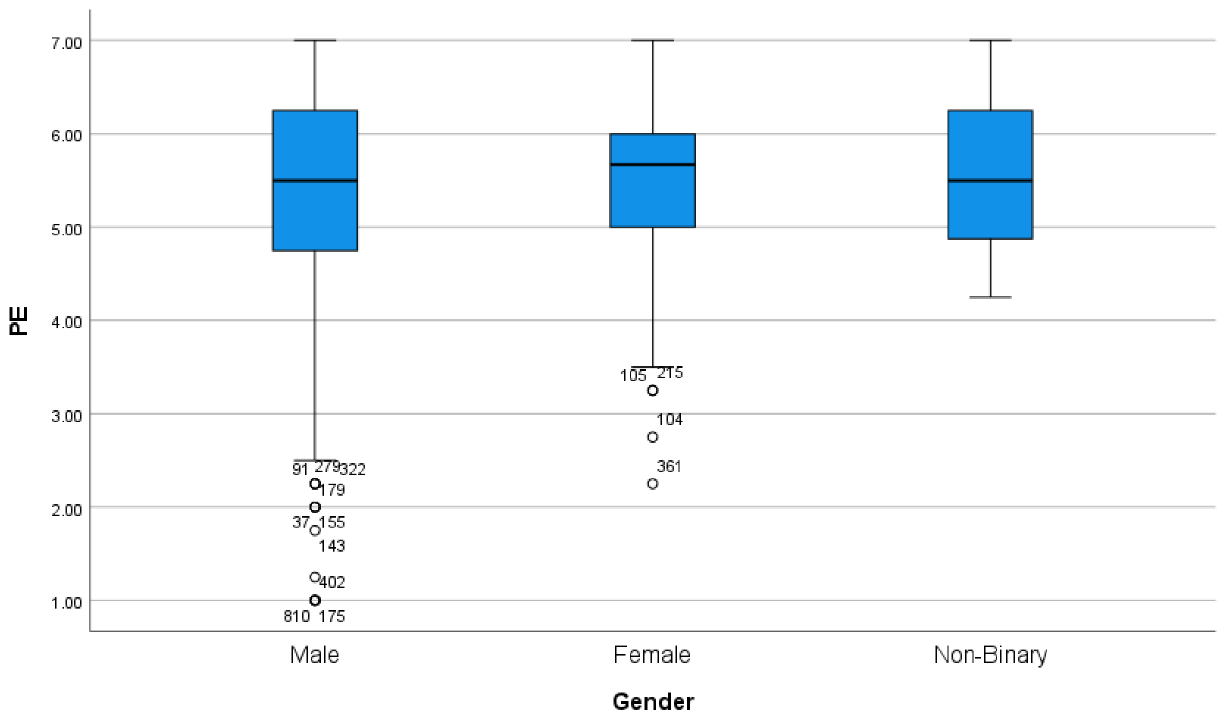
6. Signatures
Principal Investigator Kristen Haynes ______
Faculty Advisor PI, if applicable Gregory A. Harris ______

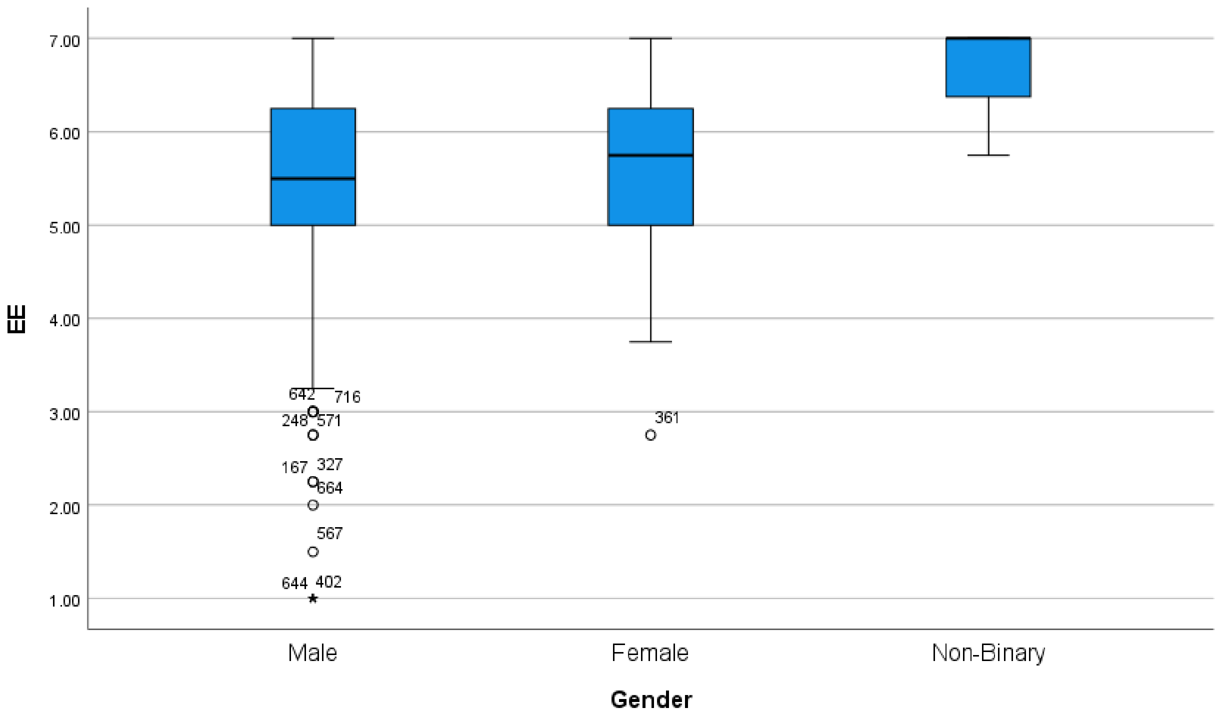
Version Date: 6/12/2022

Appendix I: SPSS Box Plot Output

Gender
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Gender	N	Percent	N	Percent	N	Percent
PE	Male	576	78.9%	154	21.1%	730	100.0%
	Female	63	71.6%	25	28.4%	88	100.0%
	Non-Binary	3	75.0%	1	25.0%	4	100.0%
EE	Male	576	78.9%	154	21.1%	730	100.0%
	Female	63	71.6%	25	28.4%	88	100.0%
	Non-Binary	3	75.0%	1	25.0%	4	100.0%
SI	Male	576	78.9%	154	21.1%	730	100.0%
	Female	63	71.6%	25	28.4%	88	100.0%
	Non-Binary	3	75.0%	1	25.0%	4	100.0%
FC	Male	576	78.9%	154	21.1%	730	100.0%
	Female	63	71.6%	25	28.4%	88	100.0%
	Non-Binary	3	75.0%	1	25.0%	4	100.0%
BI	Male	576	78.9%	154	21.1%	730	100.0%
	Female	63	71.6%	25	28.4%	88	100.0%
	Non-Binary	3	75.0%	1	25.0%	4	100.0%

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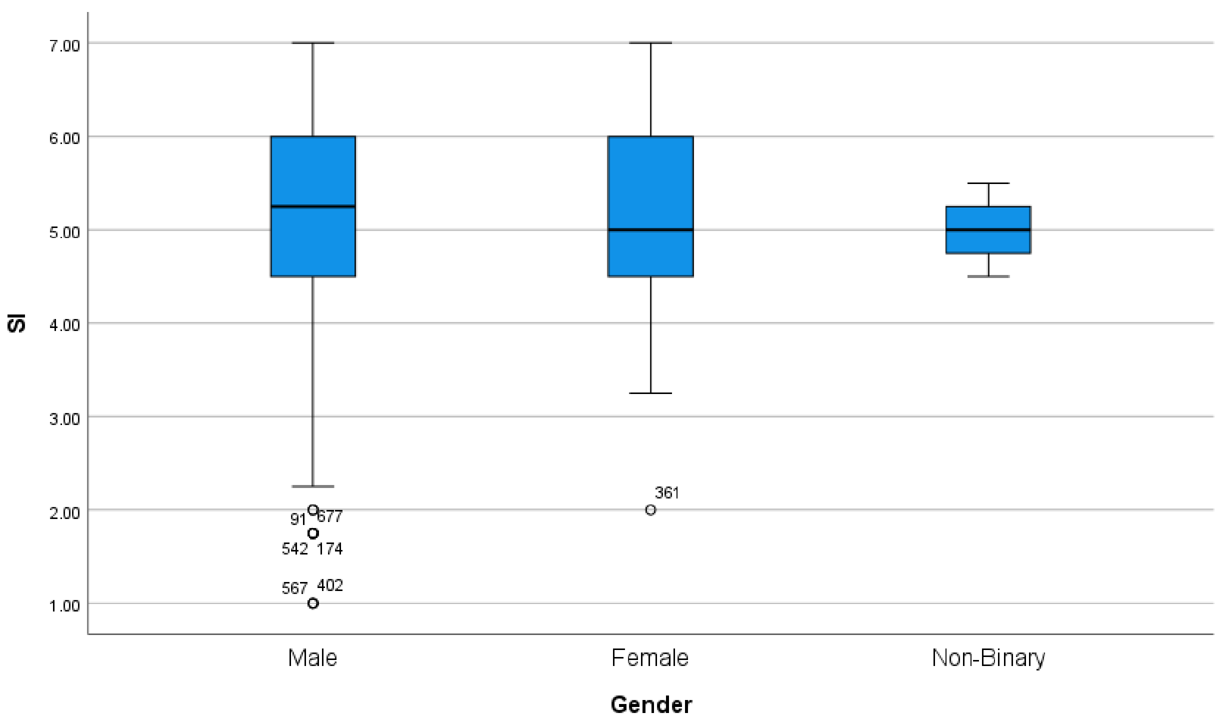
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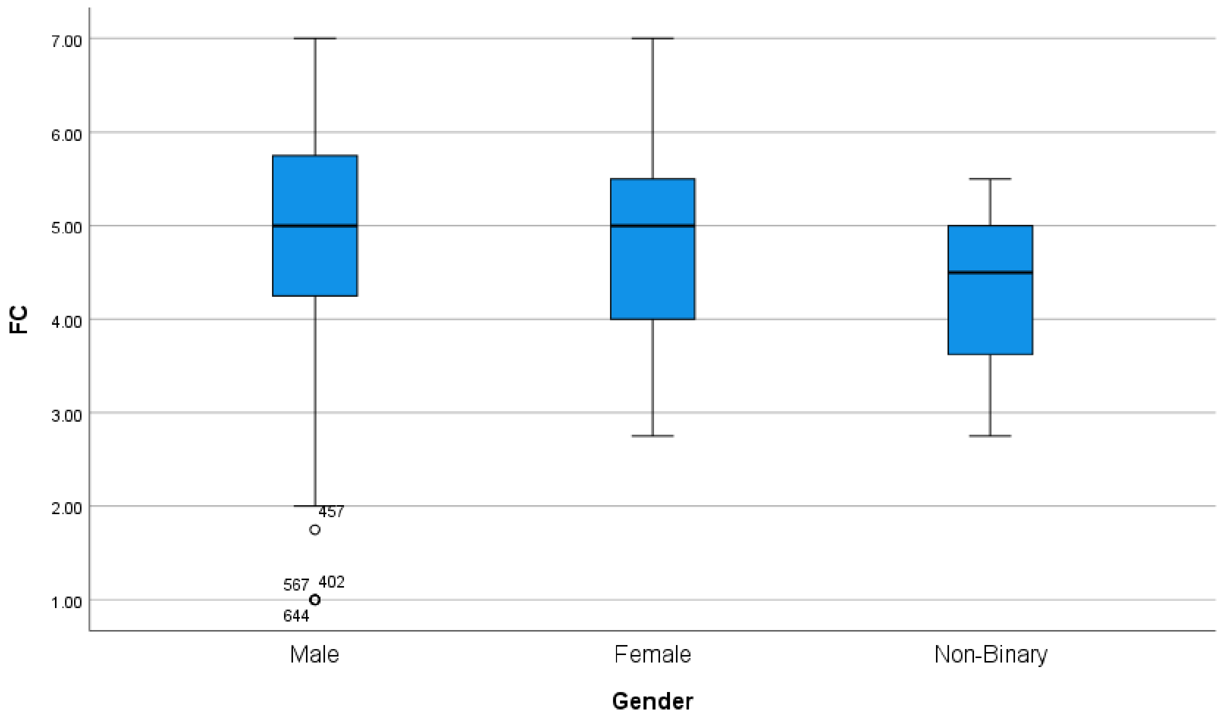

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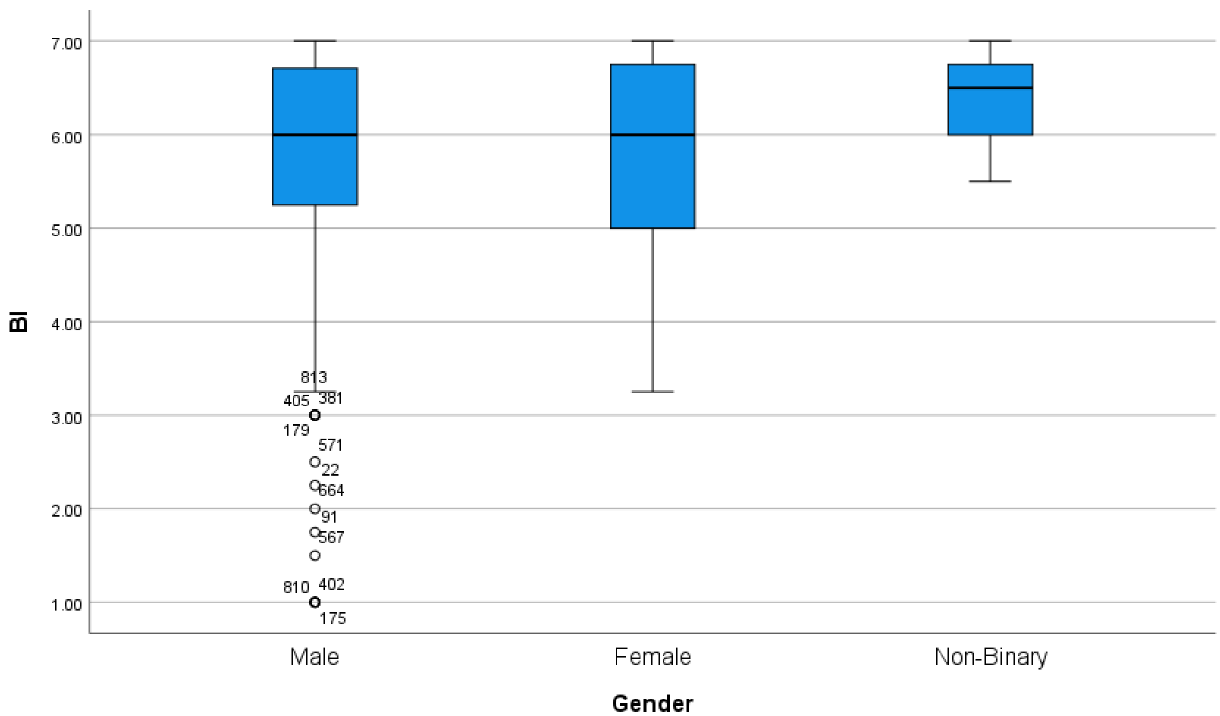

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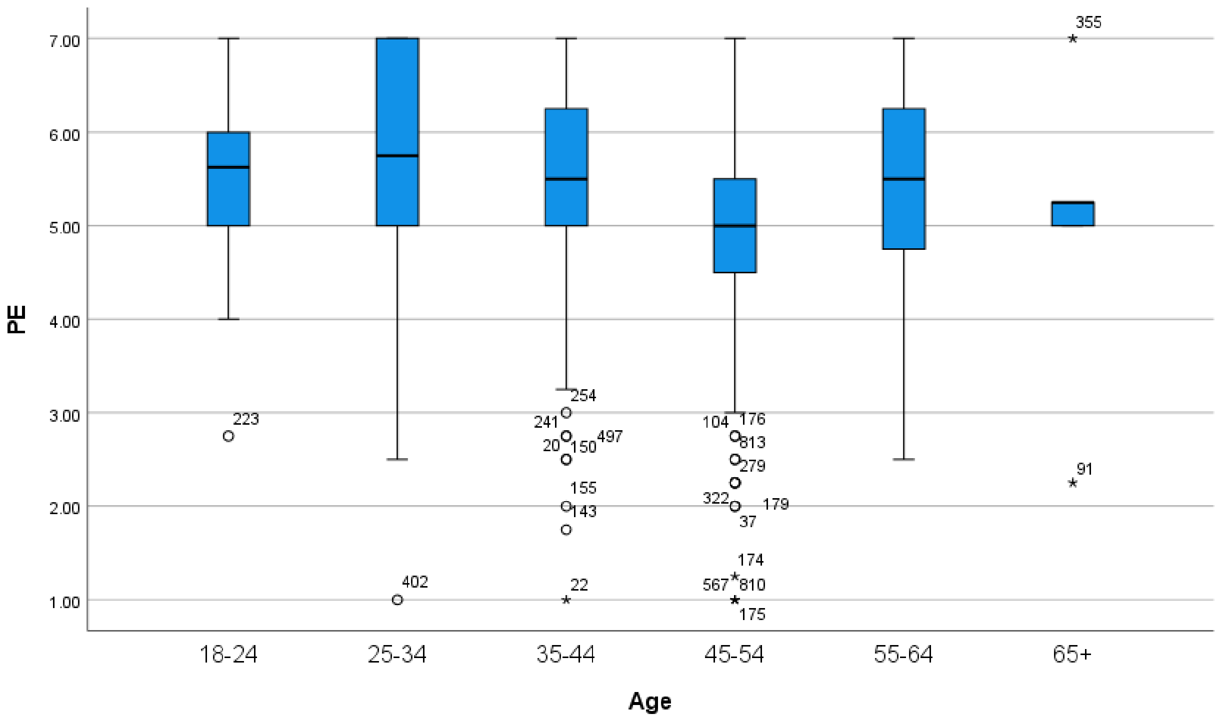
Male
Female
Non-Binary
Gender

Age

Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Age	N	Percent	N	Percent	N	Percent
PE	18-24	24	75.0%	8	25.0%	32	100.0%
	25-34	187	75.7%	60	24.3%	247	100.0%
	35-44	181	76.4%	56	23.6%	237	100.0%
	45-54	174	79.5%	45	20.5%	219	100.0%
	55-64	70	86.4%	11	13.6%	81	100.0%
	65+	6	100.0%	0	0.0%	6	100.0%
EE	18-24	24	75.0%	8	25.0%	32	100.0%
	25-34	187	75.7%	60	24.3%	247	100.0%
	35-44	181	76.4%	56	23.6%	237	100.0%
	45-54	174	79.5%	45	20.5%	219	100.0%
	55-64	70	86.4%	11	13.6%	81	100.0%
	65+	6	100.0%	0	0.0%	6	100.0%
SI	18-24	24	75.0%	8	25.0%	32	100.0%
	25-34	187	75.7%	60	24.3%	247	100.0%
	35-44	181	76.4%	56	23.6%	237	100.0%
	45-54	174	79.5%	45	20.5%	219	100.0%
	55-64	70	86.4%	11	13.6%	81	100.0%
	65+	6	100.0%	0	0.0%	6	100.0%
FC	18-24	24	75.0%	8	25.0%	32	100.0%
	25-34	187	75.7%	60	24.3%	247	100.0%
	35-44	181	76.4%	56	23.6%	237	100.0%
	45-54	174	79.5%	45	20.5%	219	100.0%
	55-64	70	86.4%	11	13.6%	81	100.0%
	65+	6	100.0%	0	0.0%	6	100.0%
BI	18-24	24	75.0%	8	25.0%	32	100.0%
	25-34	187	75.7%	60	24.3%	247	100.0%
	35-44	181	76.4%	56	23.6%	237	100.0%
	45-54	174	79.5%	45	20.5%	219	100.0%
	55-64	70	86.4%	11	13.6%	81	100.0%
	65+	6	100.0%	0	0.0%	6	100.0%



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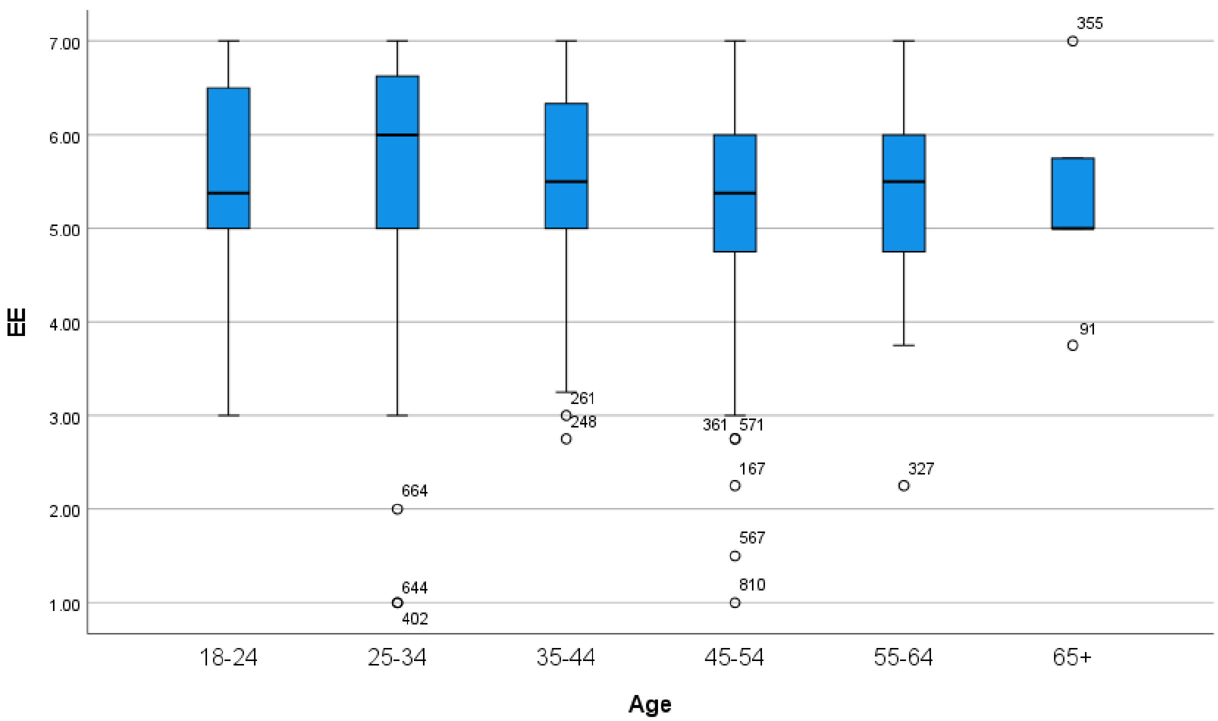

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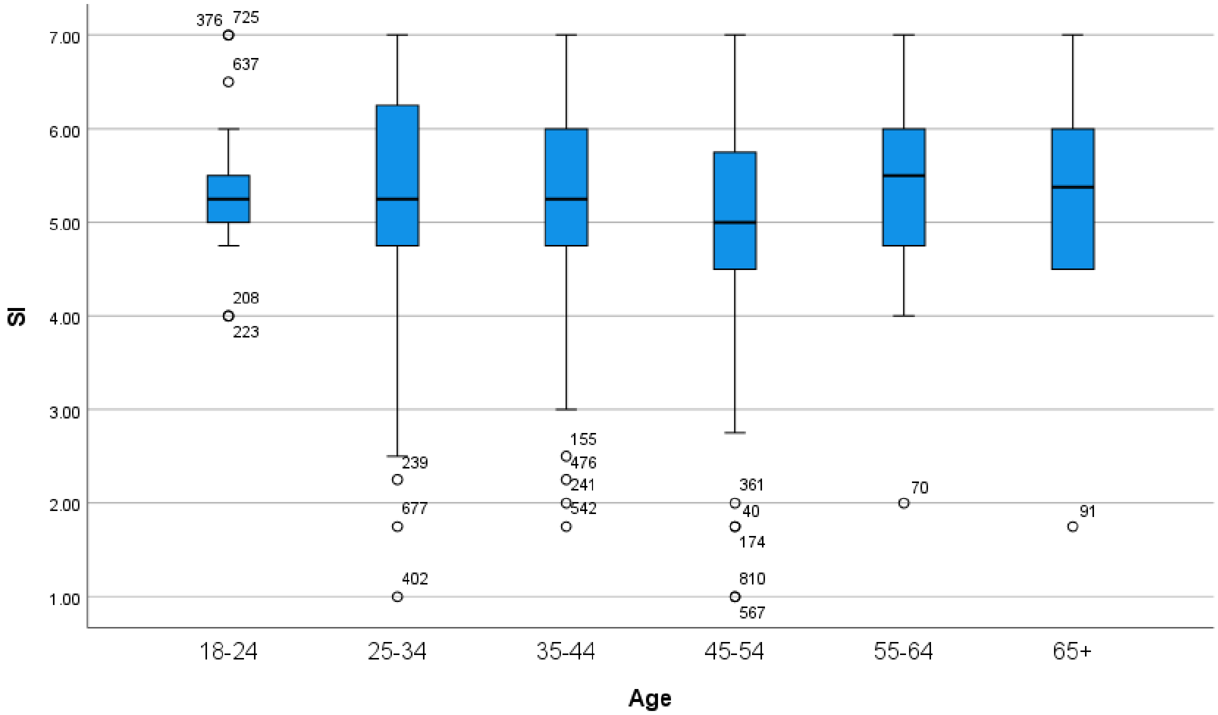
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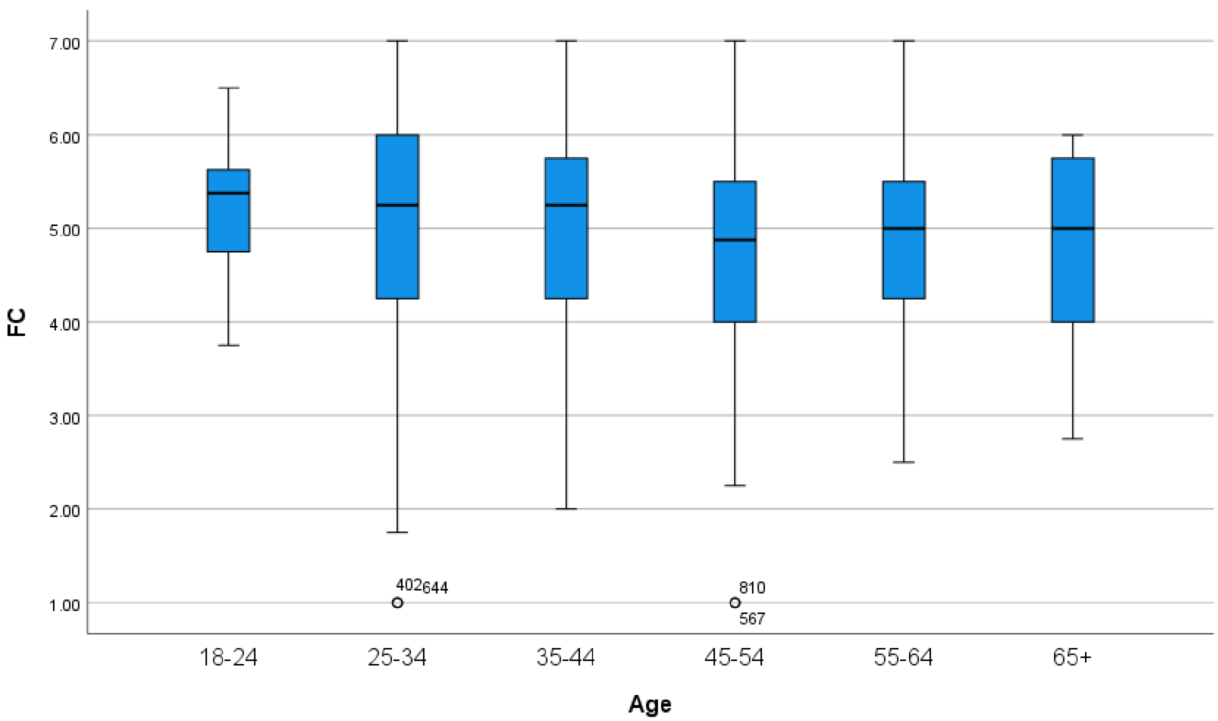
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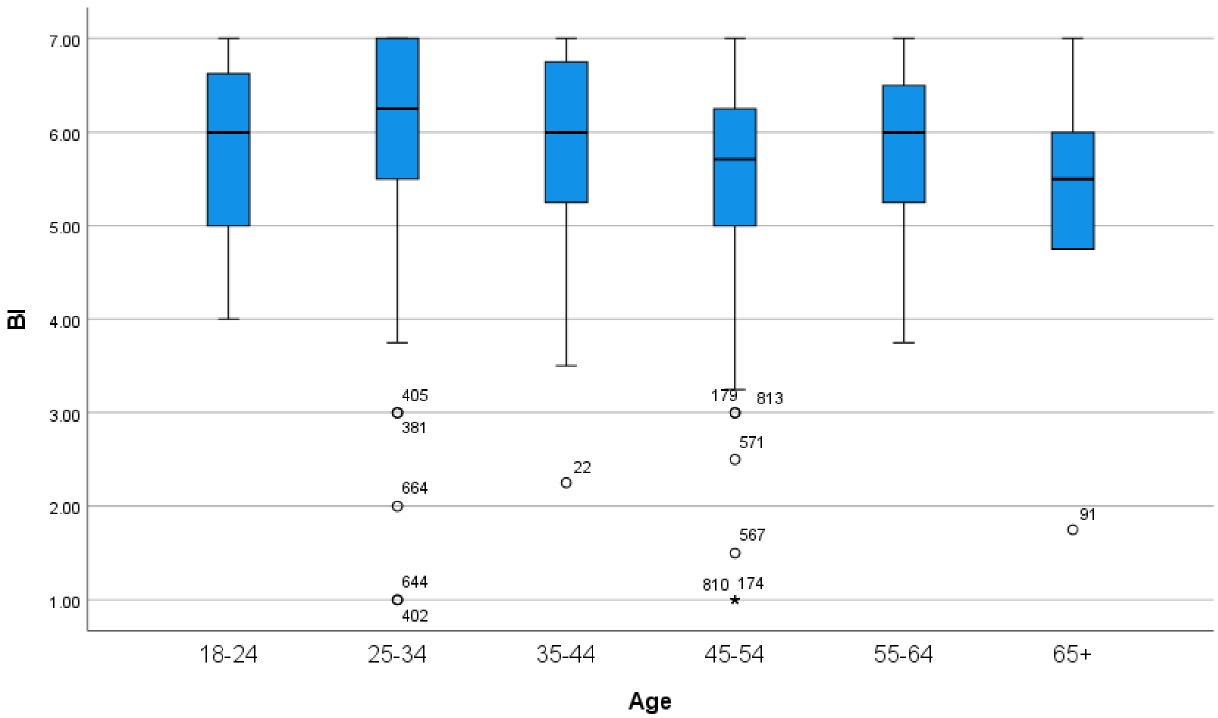

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Region

Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Region	N	Percent	N	Percent	N	Percent
PE	United States	300	82.2%	65	17.8%	365	100.0%
	Mexico	342	74.7%	116	25.3%	458	100.0%
EE	United States	300	82.2%	65	17.8%	365	100.0%
	Mexico	342	74.7%	116	25.3%	458	100.0%
SI	United States	300	82.2%	65	17.8%	365	100.0%
	Mexico	342	74.7%	116	25.3%	458	100.0%
FC	United States	300	82.2%	65	17.8%	365	100.0%
	Mexico	342	74.7%	116	25.3%	458	100.0%
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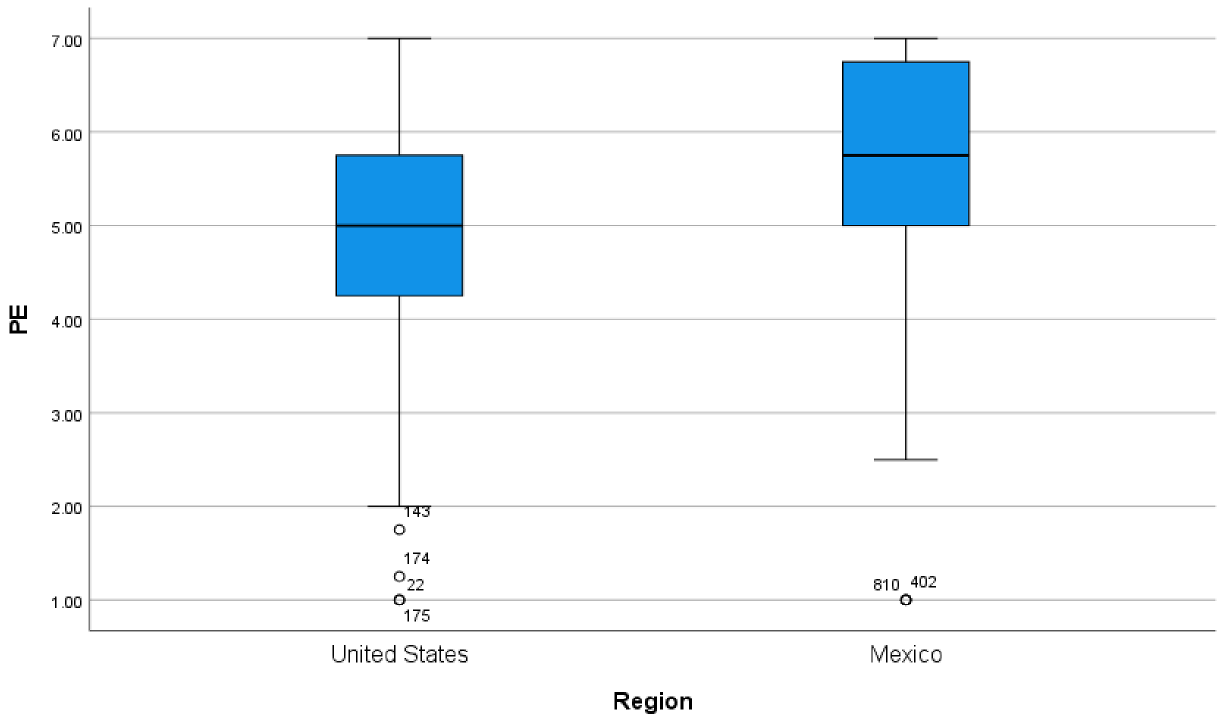
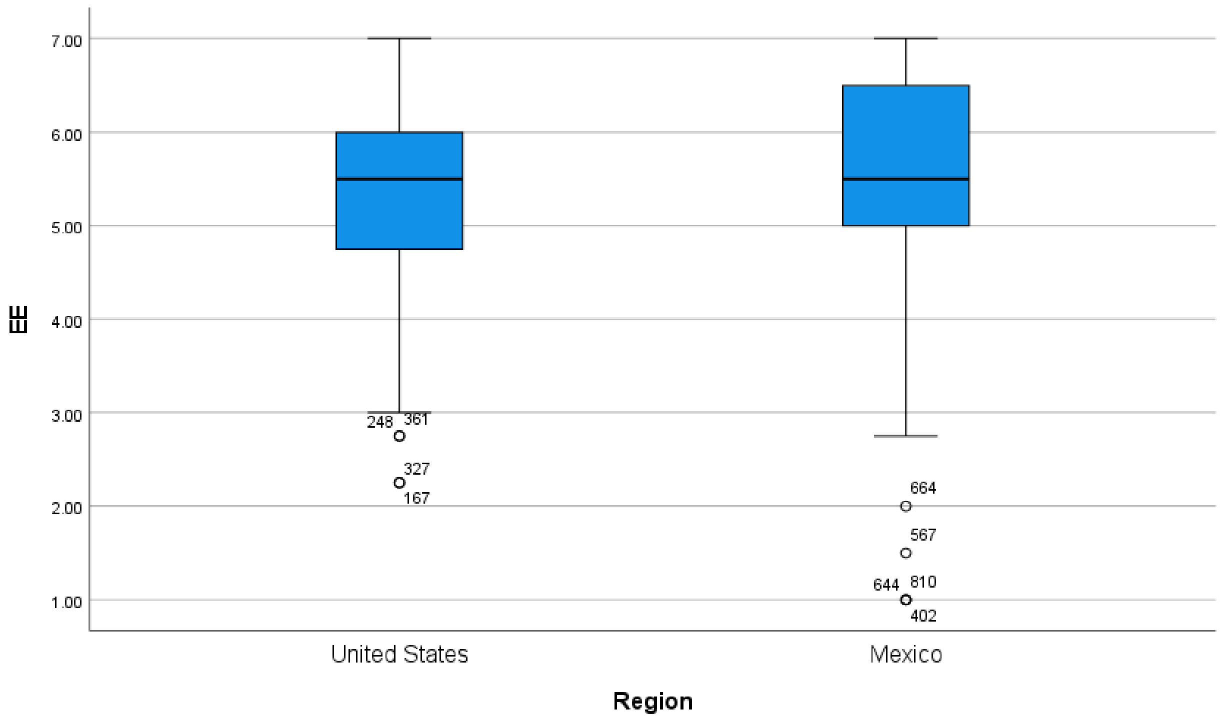
	Mexico	342	74.7%	116	25.3%	458	100.0%

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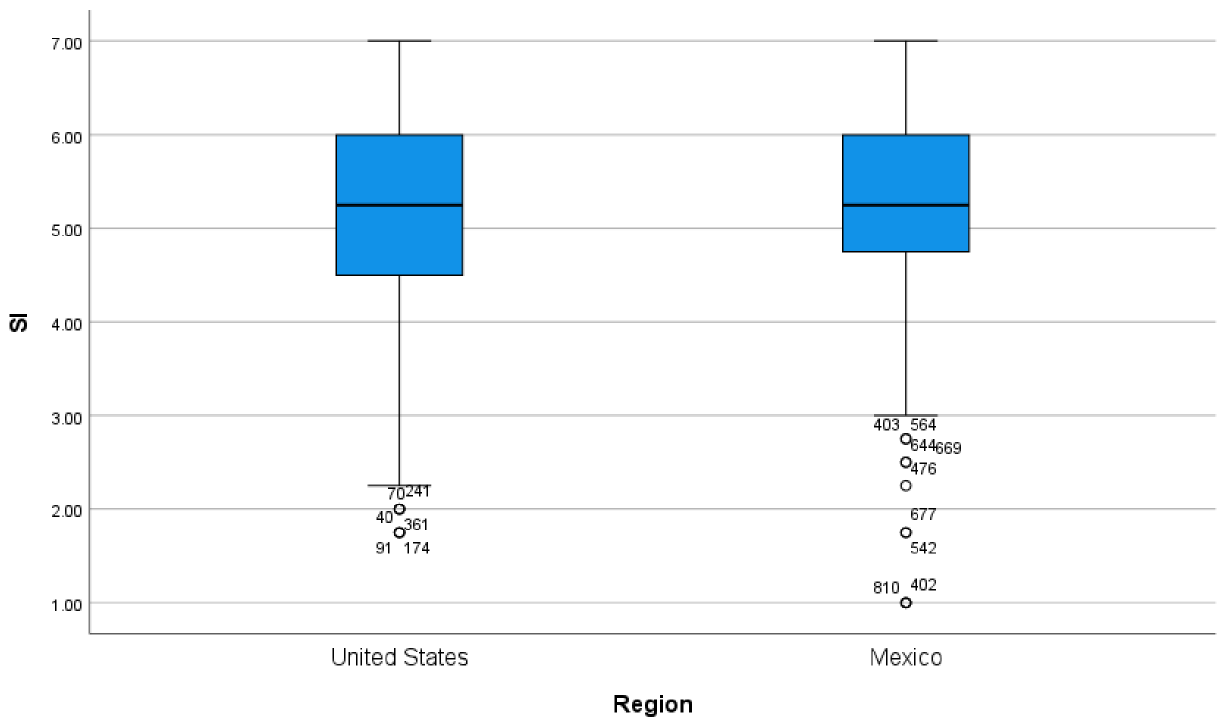
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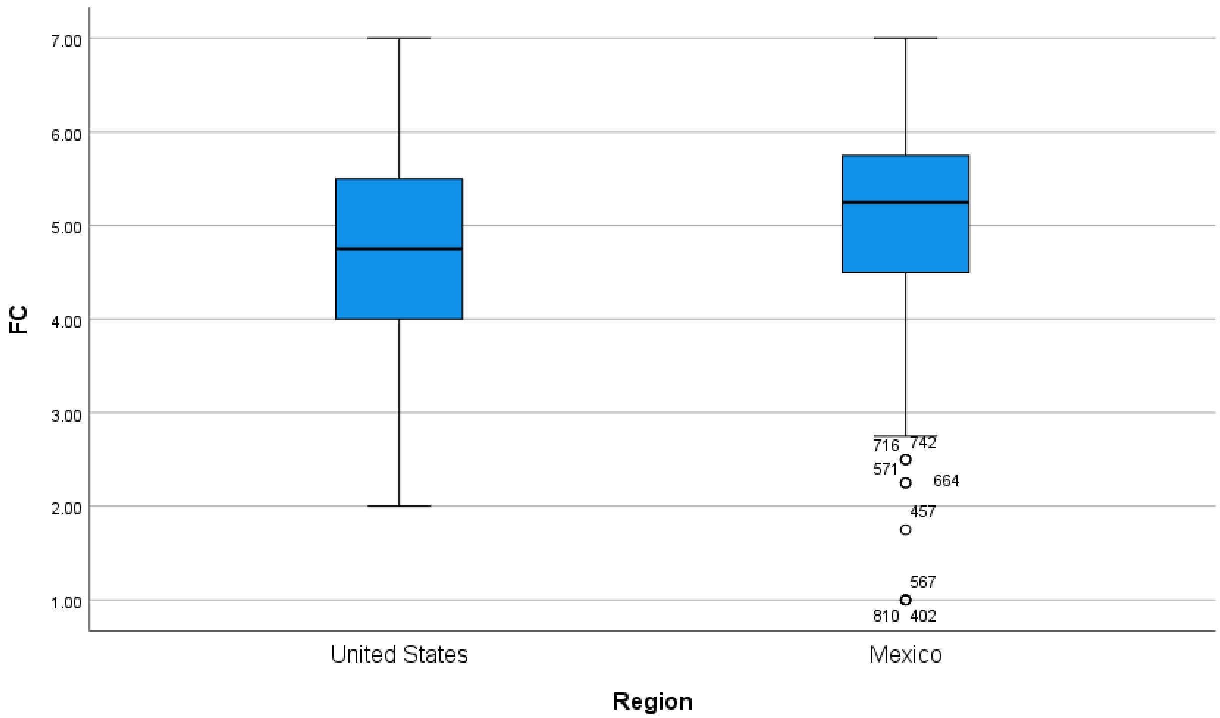
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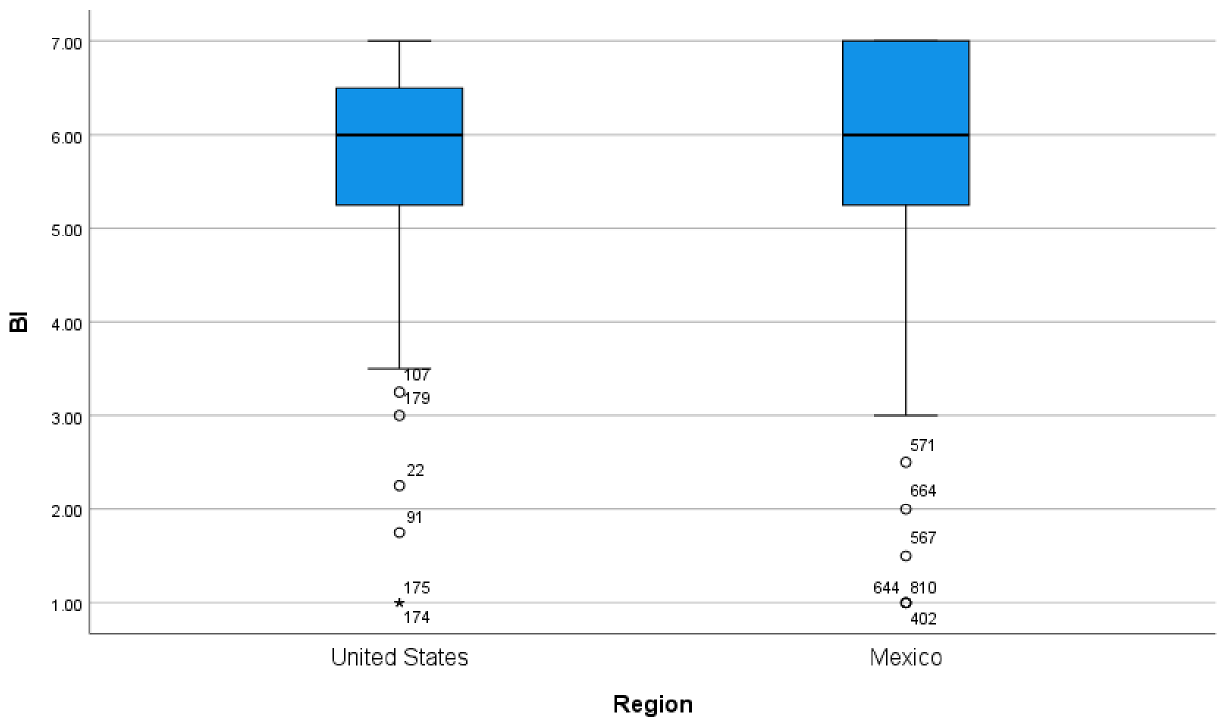
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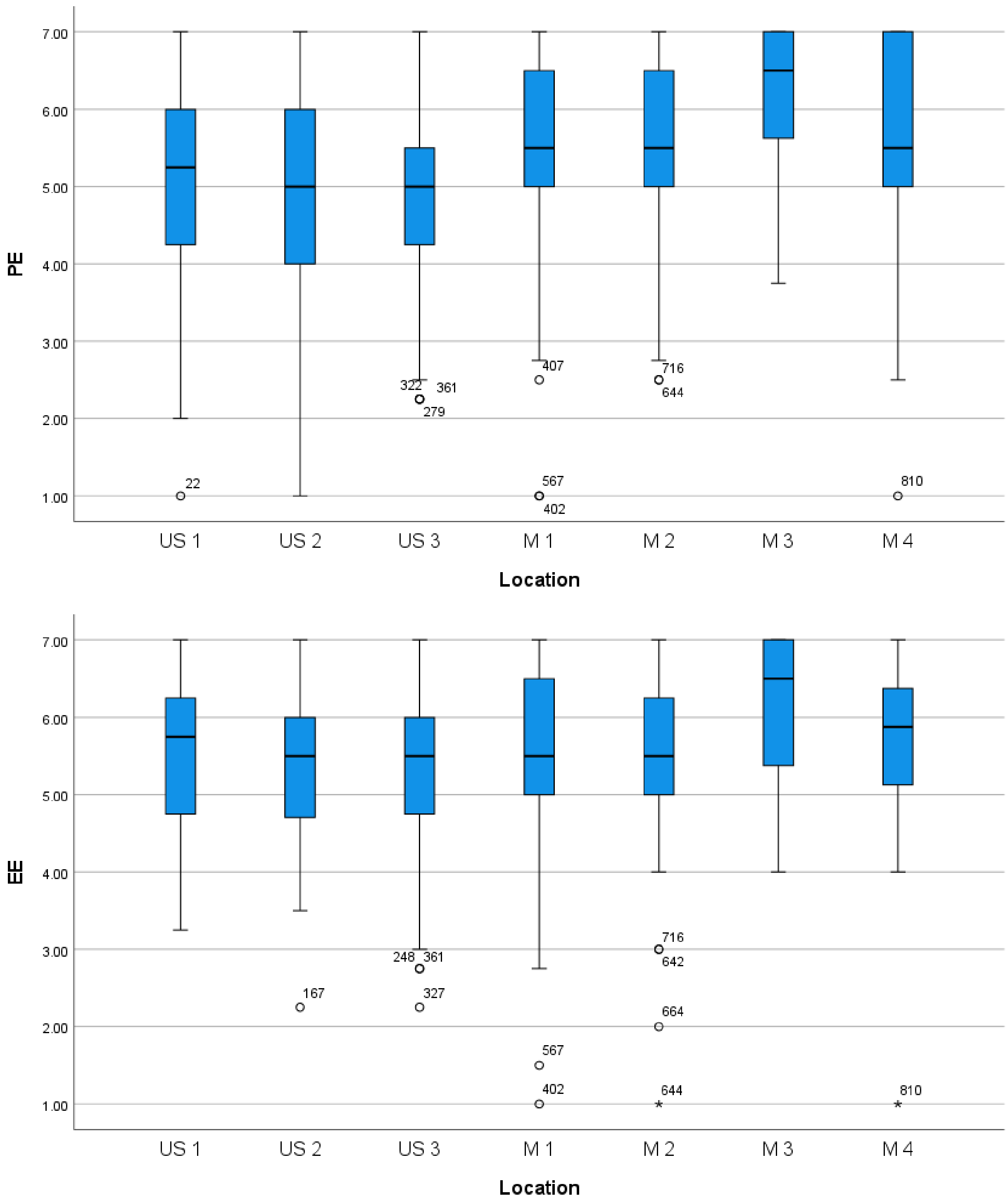
Location

Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Location	N	Percent	N	Percent	N	Percent
PE	US 1	97	84.3%	18	15.7%	115	100.0%
	US 2	79	73.8%	28	26.2%	107	100.0%
	US 3	124	86.7%	19	13.3%	143	100.0%
	M 1	206	76.0%	65	24.0%	271	100.0%
	M 2	73	83.0%	15	17.0%	88	100.0%
	M 3	51	69.9%	22	30.1%	73	100.0%
	M 4	12	57.1%	9	42.9%	21	100.0%
EE	US 1	97	84.3%	18	15.7%	115	100.0%
	US 2	79	73.8%	28	26.2%	107	100.0%
	US 3	124	86.7%	19	13.3%	143	100.0%
	M 1	206	76.0%	65	24.0%	271	100.0%
	M 2	73	83.0%	15	17.0%	88	100.0%
	M 3	51	69.9%	22	30.1%	73	100.0%
	M 4	12	57.1%	9	42.9%	21	100.0%
SI	US 1	97	84.3%	18	15.7%	115	100.0%
	US 2	79	73.8%	28	26.2%	107	100.0%
	US 3	124	86.7%	19	13.3%	143	100.0%
	M 1	206	76.0%	65	24.0%	271	100.0%
	M 2	73	83.0%	15	17.0%	88	100.0%
	M 3	51	69.9%	22	30.1%	73	100.0%
	M 4	12	57.1%	9	42.9%	21	100.0%
FC	US 1	97	84.3%	18	15.7%	115	100.0%
	US 2	79	73.8%	28	26.2%	107	100.0%
	US 3	124	86.7%	19	13.3%	143	100.0%
	M 1	206	76.0%	65	24.0%	271	100.0%
	M 2	73	83.0%	15	17.0%	88	100.0%
	M 3	51	69.9%	22	30.1%	73	100.0%
	M 4	12	57.1%	9	42.9%	21	100.0%
BI	US 1	97	84.3%	18	15.7%	115	100.0%
	US 2	79	73.8%	28	26.2%	107	100.0%
	US 3	124	86.7%	19	13.3%	143	100.0%
	M 1	206	76.0%	65	24.0%	271	100.0%
	M 2	73	83.0%	15	17.0%	88	100.0%
	M 3	51	69.9%	22	30.1%	73	100.0%
	M 4	12	57.1%	9	42.9%	21	100.0%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Location
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US 1
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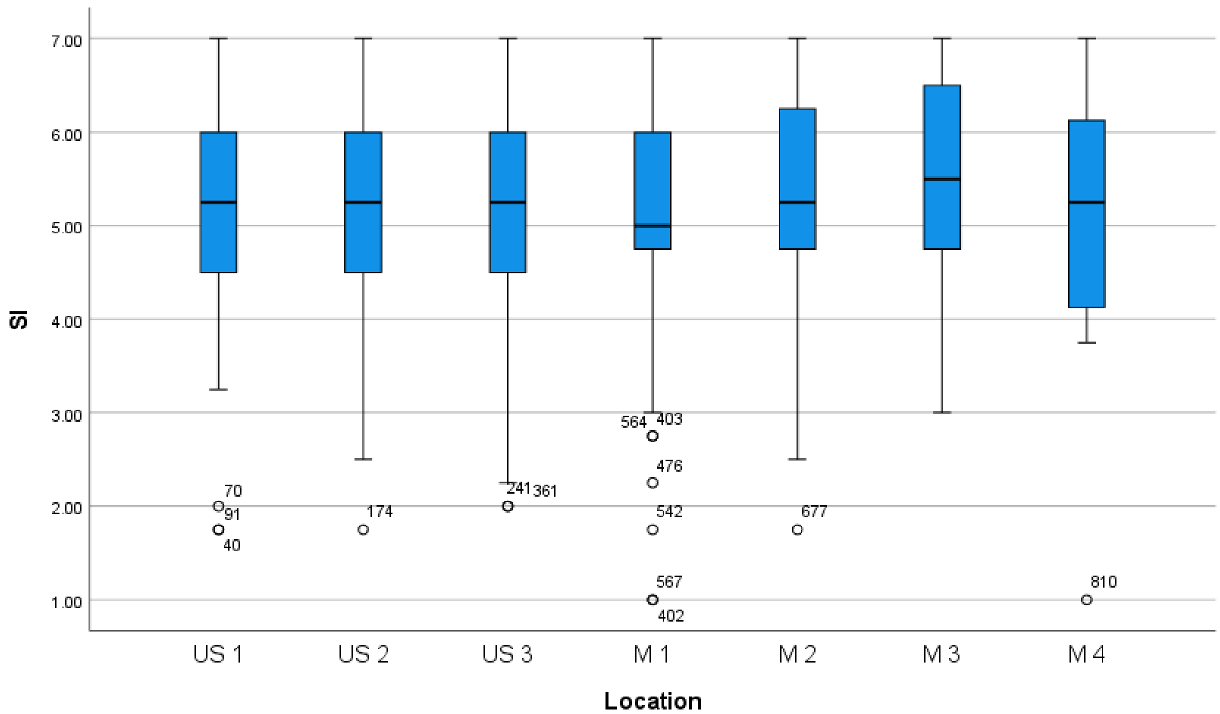
Location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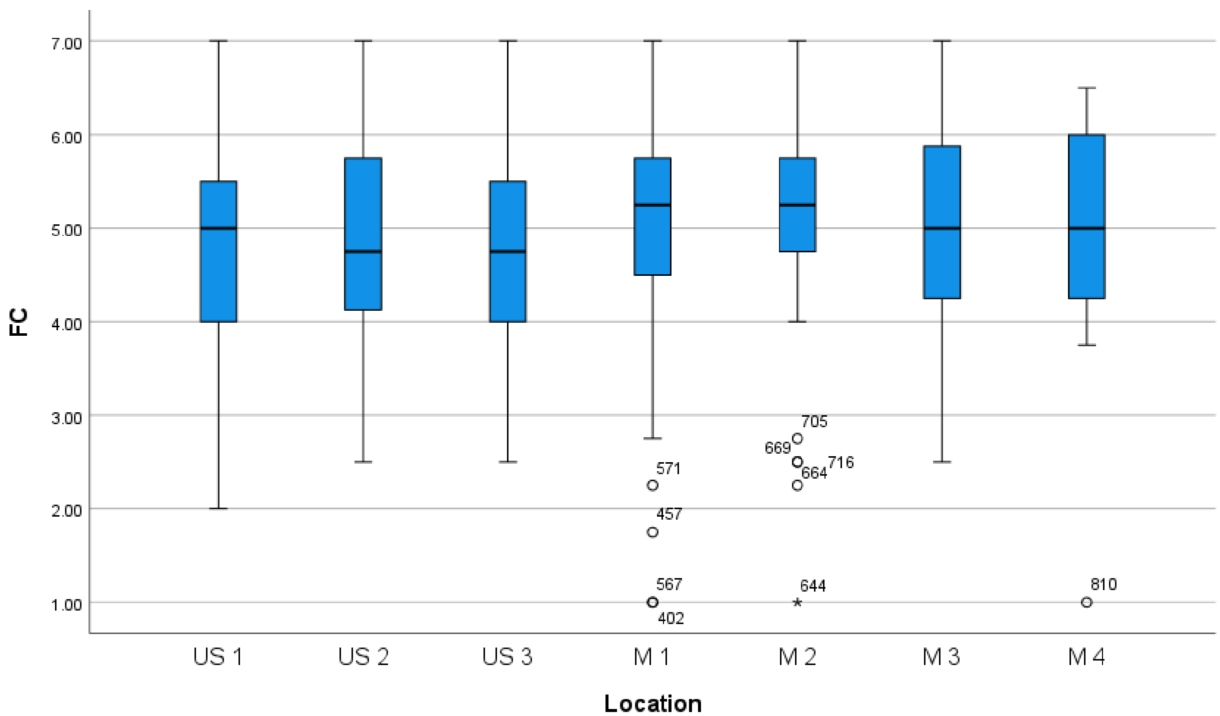
Location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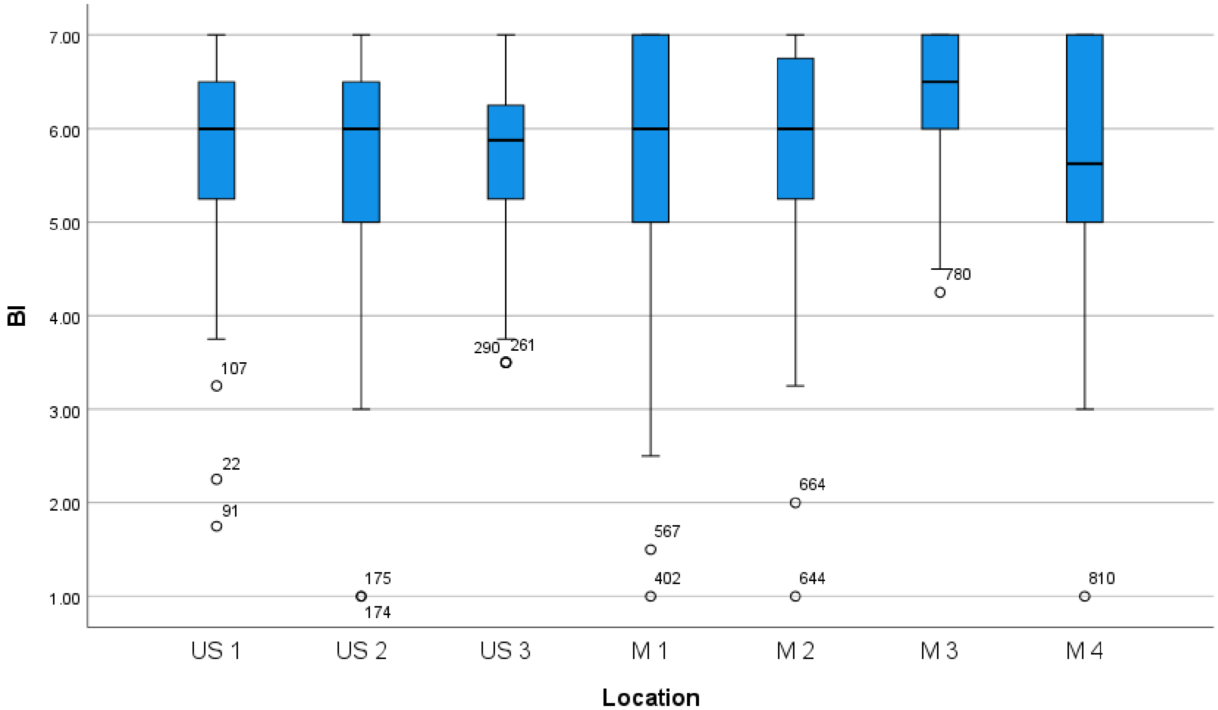
Location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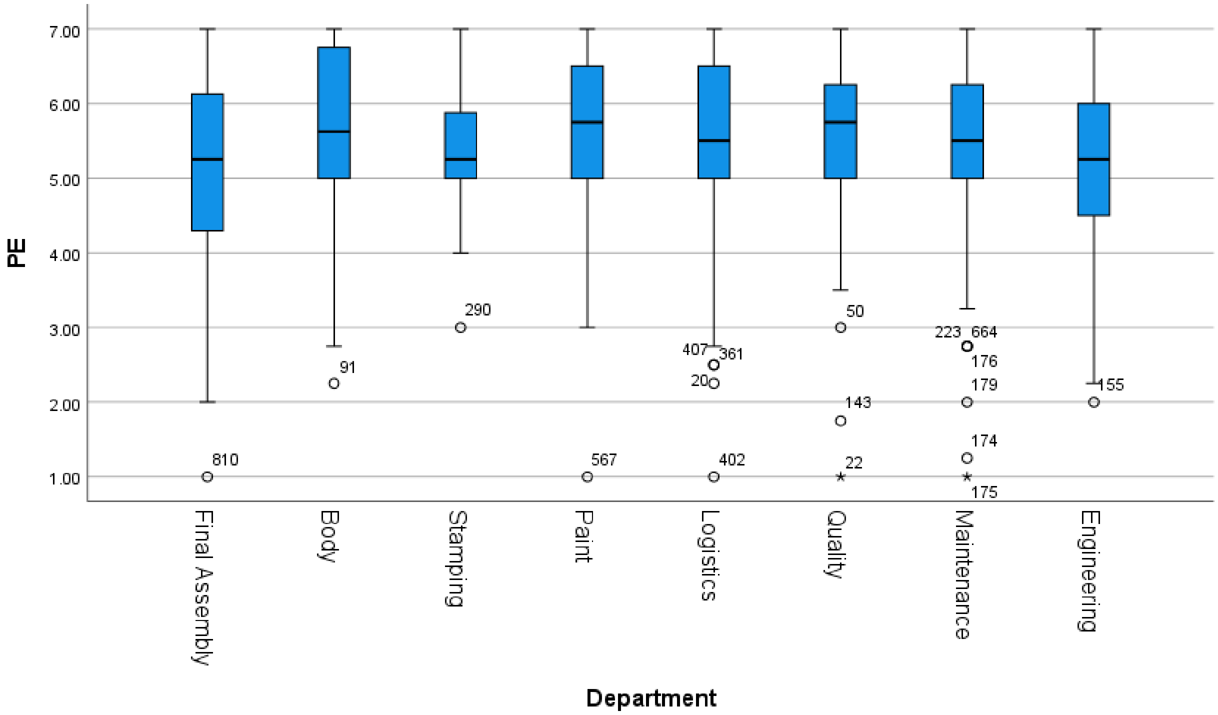
US 1
US 2
US 3
M 1
M 2
M 3
M 4
Location

Department

Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Department	N	Percent	N	Percent	N	Percent
PE	Final Assembly	76	81.7%	17	18.3%	93	100.0%
	Body	62	91.2%	6	8.8%	68	100.0%
	Stamping	23	74.2%	8	25.8%	31	100.0%
	Paint	40	83.3%	8	16.7%	48	100.0%
	Logistics	66	81.5%	15	18.5%	81	100.0%
	Quality	74	90.2%	8	9.8%	82	100.0%
	Maintenance	117	92.9%	9	7.1%	126	100.0%
	Engineering	184	84.4%	34	15.6%	218	100.0%
EE	Final Assembly	76	81.7%	17	18.3%	93	100.0%
	Body	62	91.2%	6	8.8%	68	100.0%
	Stamping	23	74.2%	8	25.8%	31	100.0%
	Paint	40	83.3%	8	16.7%	48	100.0%
	Logistics	66	81.5%	15	18.5%	81	100.0%
	Quality	74	90.2%	8	9.8%	82	100.0%
	Maintenance	117	92.9%	9	7.1%	126	100.0%
	Engineering	184	84.4%	34	15.6%	218	100.0%
SI	Final Assembly	76	81.7%	17	18.3%	93	100.0%
	Body	62	91.2%	6	8.8%	68	100.0%
	Stamping	23	74.2%	8	25.8%	31	100.0%
	Paint	40	83.3%	8	16.7%	48	100.0%
	Logistics	66	81.5%	15	18.5%	81	100.0%
	Quality	74	90.2%	8	9.8%	82	100.0%
	Maintenance	117	92.9%	9	7.1%	126	100.0%
	Engineering	184	84.4%	34	15.6%	218	100.0%
FC	Final Assembly	76	81.7%	17	18.3%	93	100.0%
	Body	62	91.2%	6	8.8%	68	100.0%
	Stamping	23	74.2%	8	25.8%	31	100.0%
	Paint	40	83.3%	8	16.7%	48	100.0%
	Logistics	66	81.5%	15	18.5%	81	100.0%
	Quality	74	90.2%	8	9.8%	82	100.0%
	Maintenance	117	92.9%	9	7.1%	126	100.0%
	Engineering	184	84.4%	34	15.6%	218	100.0%
BI	Final Assembly	76	81.7%	17	18.3%	93	100.0%
	Body	62	91.2%	6	8.8%	68	100.0%
	Stamping	23	74.2%	8	25.8%	31	100.0%
	Paint	40	83.3%	8	16.7%	48	100.0%
	Logistics	66	81.5%	15	18.5%	81	100.0%
	Quality	74	90.2%	8	9.8%	82	100.0%
	Maintenance	117	92.9%	9	7.1%	126	100.0%
	Engineering	184	84.4%	34	15.6%	218	100.0%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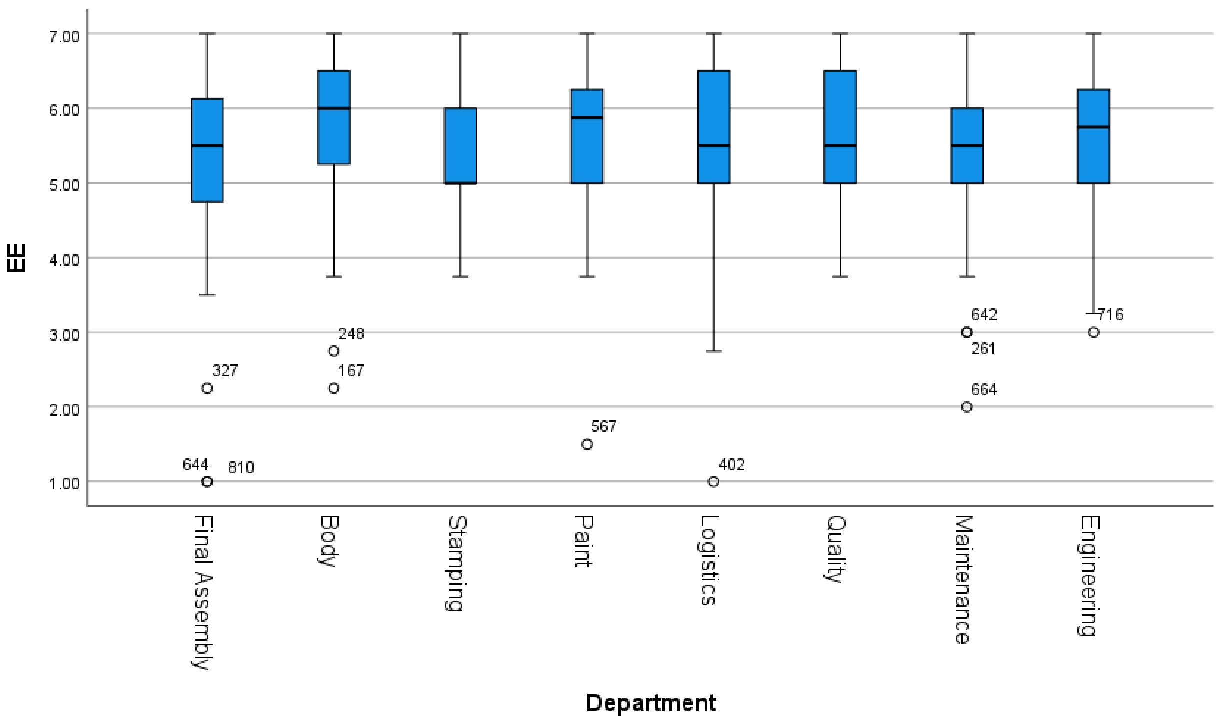
Final Assembly
Body
Stamping
Paint
Logistics
Quality
Maintenance
Engineering
Department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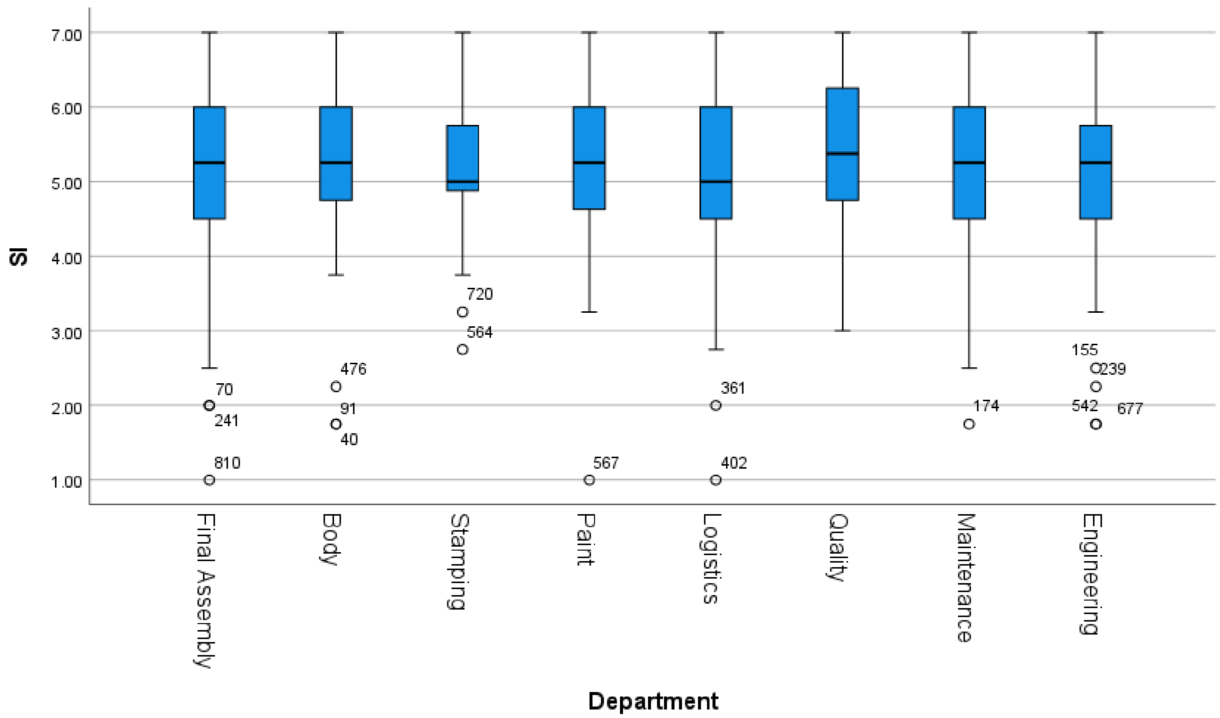
Final Assembly
Body
Stamping
Paint
Logistics
Quality
Maintenance
Engineering
Department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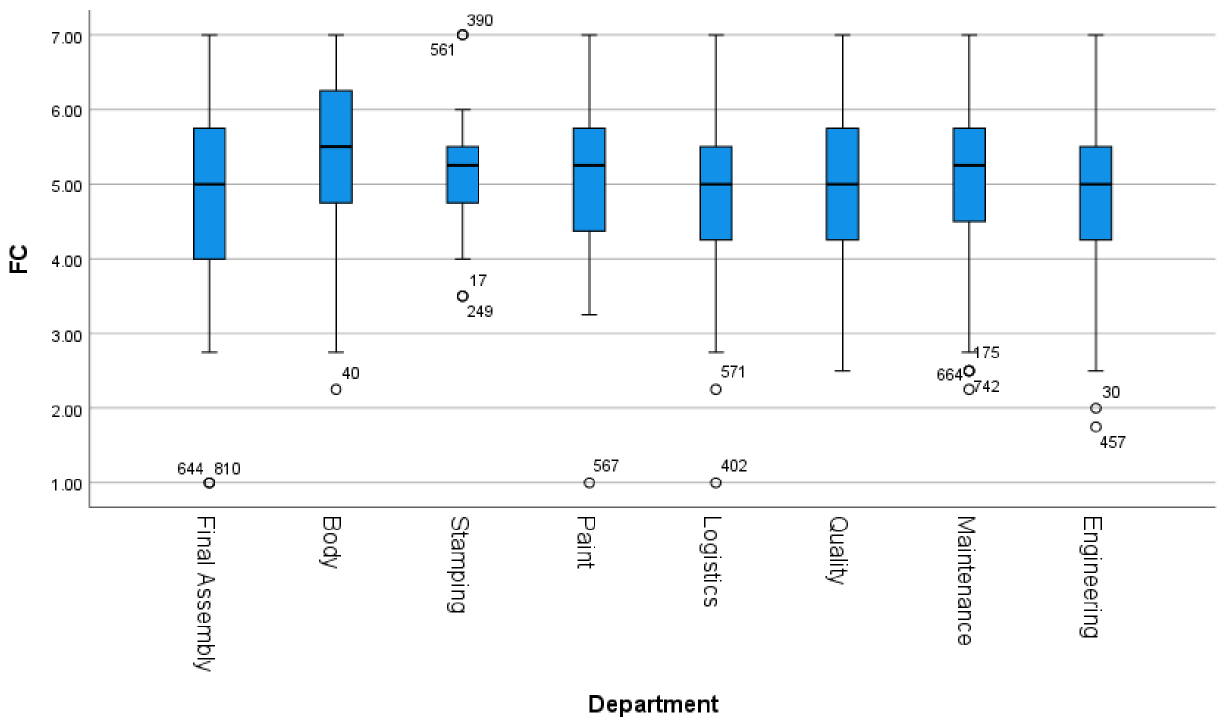
Final Assembly
Body
Stamping
Paint
Logistics
Quality
Maintenance
Engineering
Department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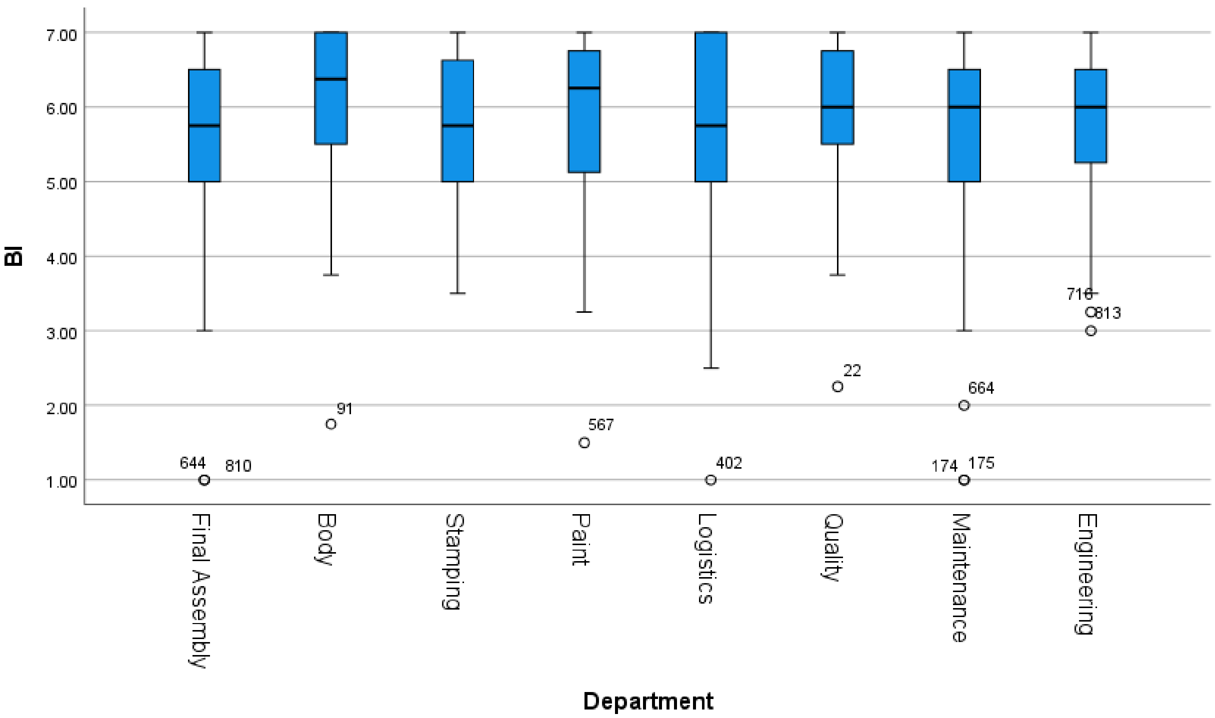
Final Assembly
Body
Stamping
Paint
Logistics
Quality
Maintenance
Engineering
Department



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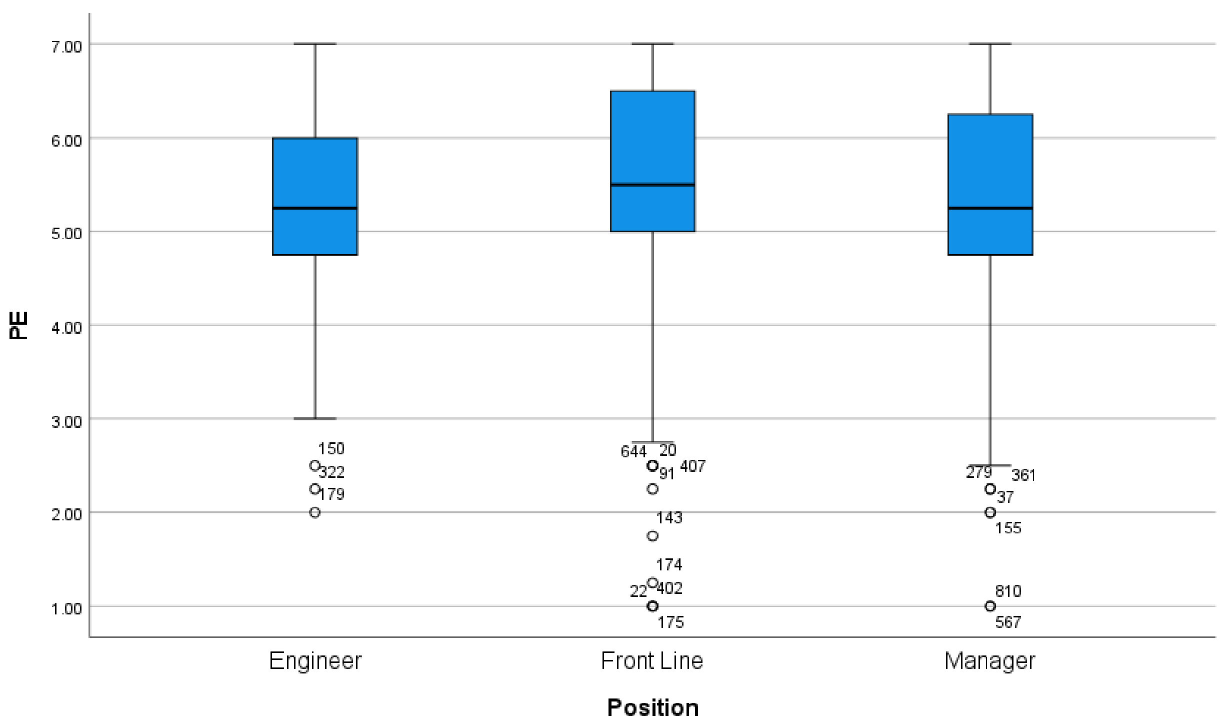
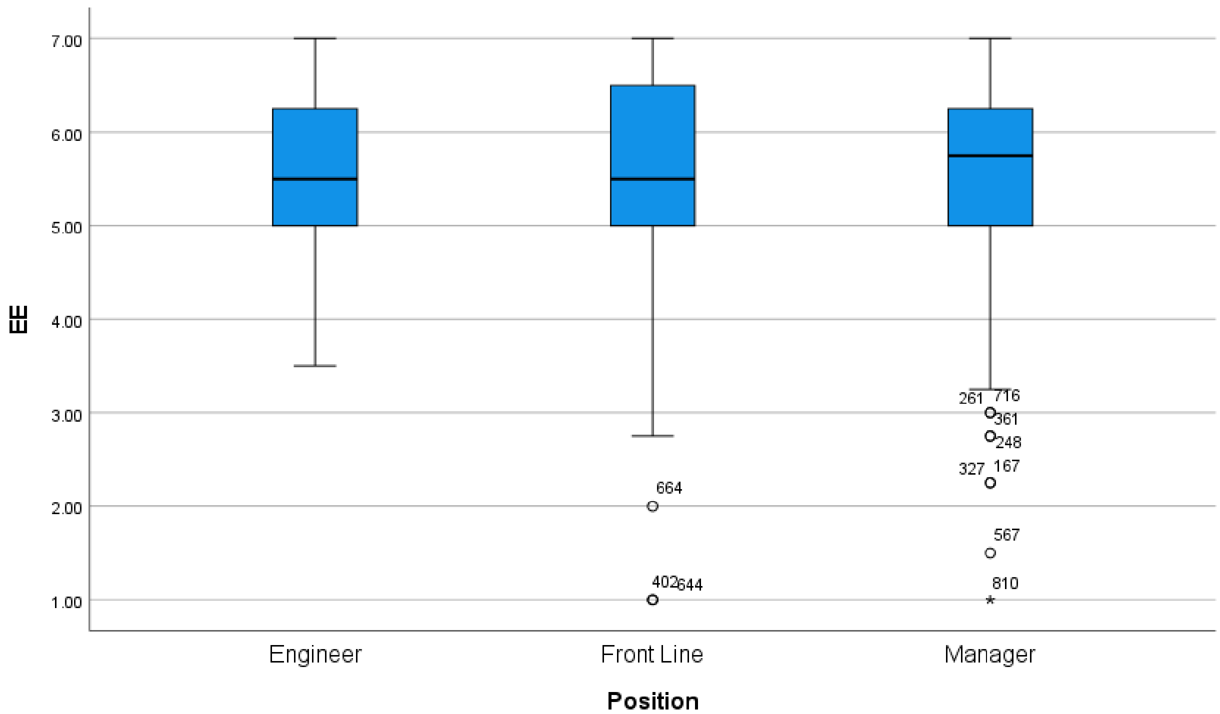
Final Assembly
Body
Stamping
Paint
Logistics
Quality
Maintenance
Engineering
Department

Job Role
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Position	N	Percent	N	Percent	N	Percent
PE	Engineer	165	75.7%	53	24.3%	218	100.0%
	Front Line	194	78.2%	54	21.8%	248	100.0%
	Manager	283	85.0%	50	15.0%	333	100.0%
EE	Engineer	165	75.7%	53	24.3%	218	100.0%
	Front Line	194	78.2%	54	21.8%	248	100.0%
	Manager	283	85.0%	50	15.0%	333	100.0%
SI	Engineer	165	75.7%	53	24.3%	218	100.0%
	Front Line	194	78.2%	54	21.8%	248	100.0%
	Manager	283	85.0%	50	15.0%	333	100.0%
FC	Engineer	165	75.7%	53	24.3%	218	100.0%
	Front Line	194	78.2%	54	21.8%	248	100.0%
	Manager	283	85.0%	50	15.0%	333	100.0%
BI	Engineer	165	75.7%	53	24.3%	218	100.0%
	Front Line	194	78.2%	54	21.8%	248	100.0%
	Manager	283	85.0%	50	15.0%	333	100.0%

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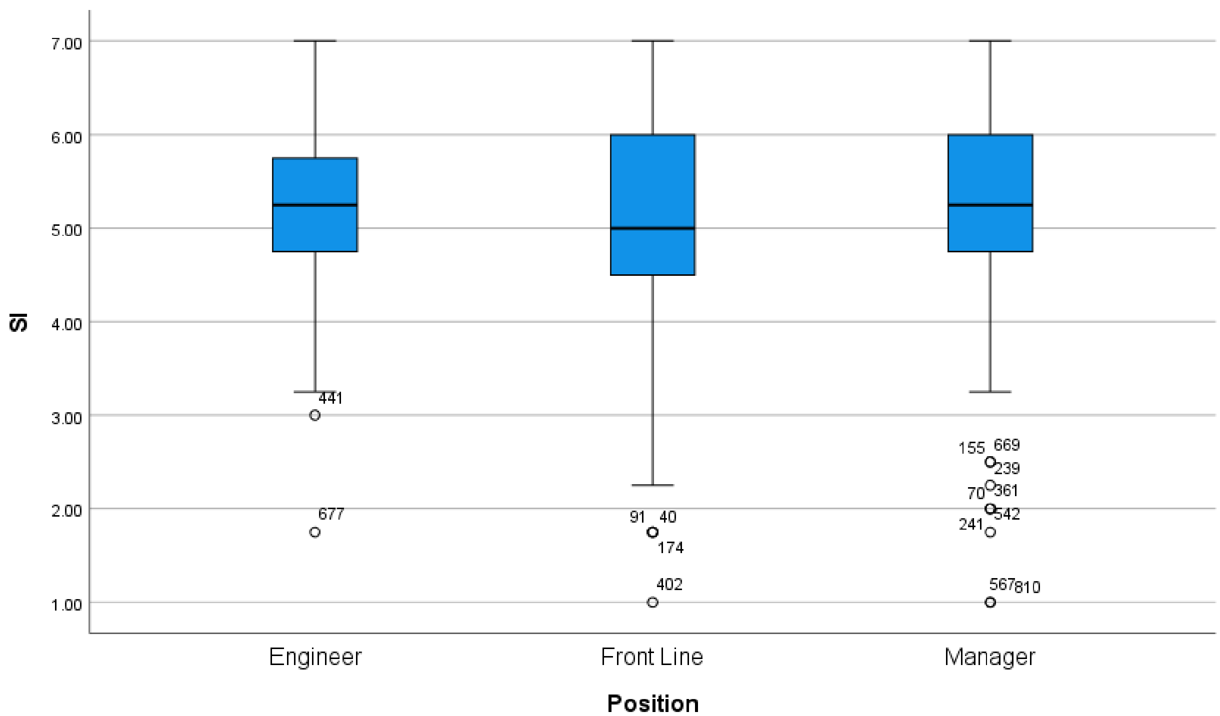
Engineer
Front Line
Manager
Position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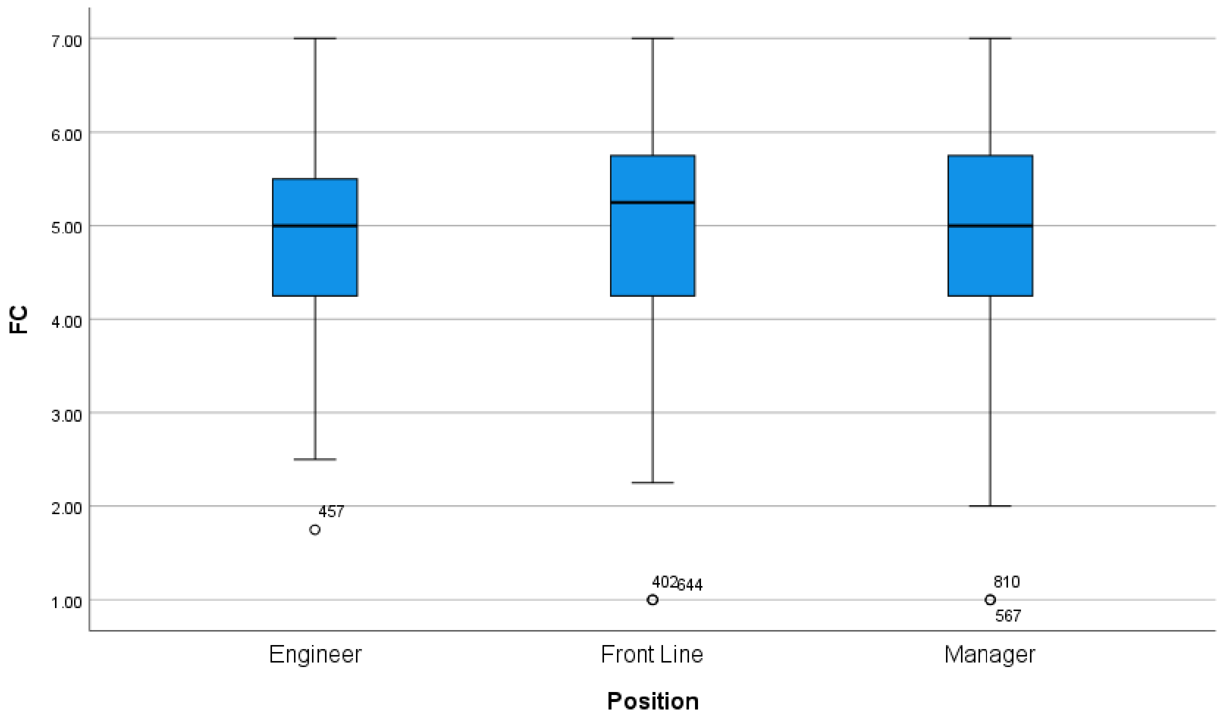
Engineer
Front Line
Manager
Position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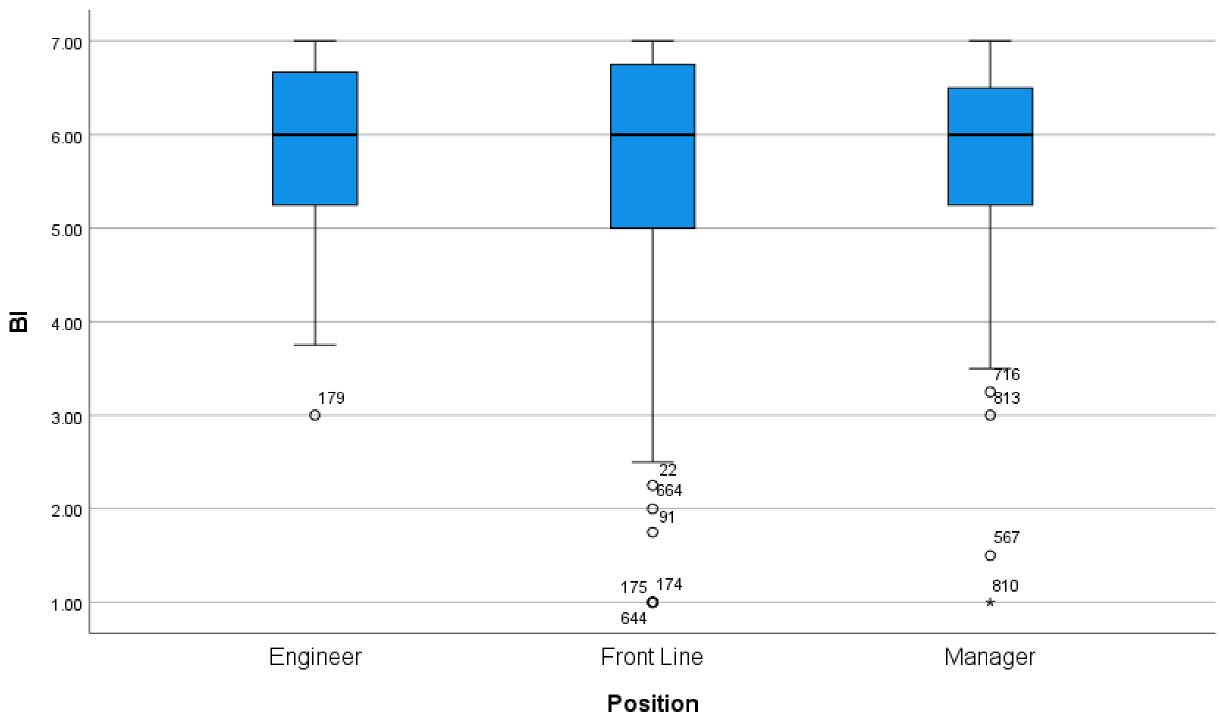
Manager
Position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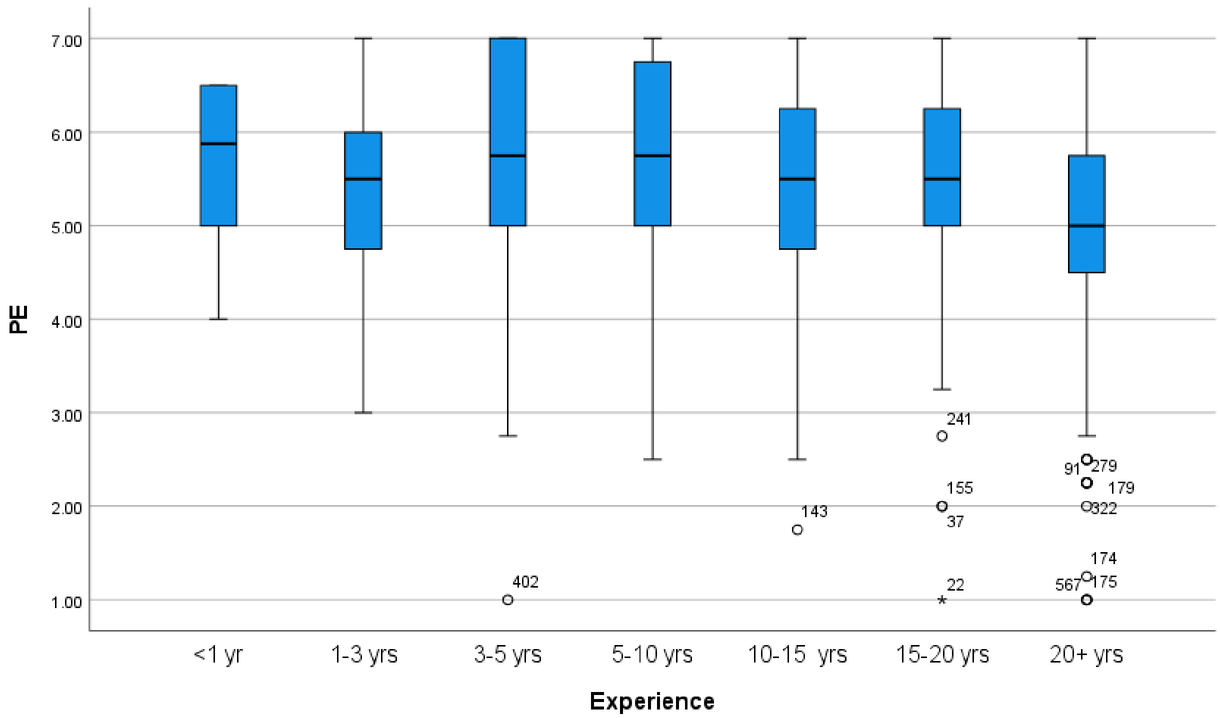
Engineer
Front Line
Manager
Position

Experience
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Experience	N	Percent	N	Percent	N	Percent
PE	<1 yr	6	100.0%	0	0.0%	6	100.0%
	1-3 yrs	33	80.5%	8	19.5%	41	100.0%
	3-5 yrs	46	86.8%	7	13.2%	53	100.0%
	5-10 yrs	142	86.6%	22	13.4%	164	100.0%
	10-15 yrs	86	90.5%	9	9.5%	95	100.0%
	15-20 yrs	108	86.4%	17	13.6%	125	100.0%
	20+ yrs	221	90.9%	22	9.1%	243	100.0%
EE	<1 yr	6	100.0%	0	0.0%	6	100.0%
	1-3 yrs	33	80.5%	8	19.5%	41	100.0%
	3-5 yrs	46	86.8%	7	13.2%	53	100.0%
	5-10 yrs	142	86.6%	22	13.4%	164	100.0%
	10-15 yrs	86	90.5%	9	9.5%	95	100.0%
	15-20 yrs	108	86.4%	17	13.6%	125	100.0%
	20+ yrs	221	90.9%	22	9.1%	243	100.0%
SI	<1 yr	6	100.0%	0	0.0%	6	100.0%
	1-3 yrs	33	80.5%	8	19.5%	41	100.0%
	3-5 yrs	46	86.8%	7	13.2%	53	100.0%
	5-10 yrs	142	86.6%	22	13.4%	164	100.0%
	10-15 yrs	86	90.5%	9	9.5%	95	100.0%
	15-20 yrs	108	86.4%	17	13.6%	125	100.0%
	20+ yrs	221	90.9%	22	9.1%	243	100.0%
FC	<1 yr	6	100.0%	0	0.0%	6	100.0%
	1-3 yrs	33	80.5%	8	19.5%	41	100.0%
	3-5 yrs	46	86.8%	7	13.2%	53	100.0%
	5-10 yrs	142	86.6%	22	13.4%	164	100.0%
	10-15 yrs	86	90.5%	9	9.5%	95	100.0%
	15-20 yrs	108	86.4%	17	13.6%	125	100.0%
	20+ yrs	221	90.9%	22	9.1%	243	100.0%
BI	<1 yr	6	100.0%	0	0.0%	6	100.0%
	1-3 yrs	33	80.5%	8	19.5%	41	100.0%
	3-5 yrs	46	86.8%	7	13.2%	53	100.0%
	5-10 yrs	142	86.6%	22	13.4%	164	100.0%
	10-15 yrs	86	90.5%	9	9.5%	95	100.0%
	15-20 yrs	108	86.4%	17	13.6%	125	100.0%
	20+ yrs	221	90.9%	22	9.1%	243	100.0%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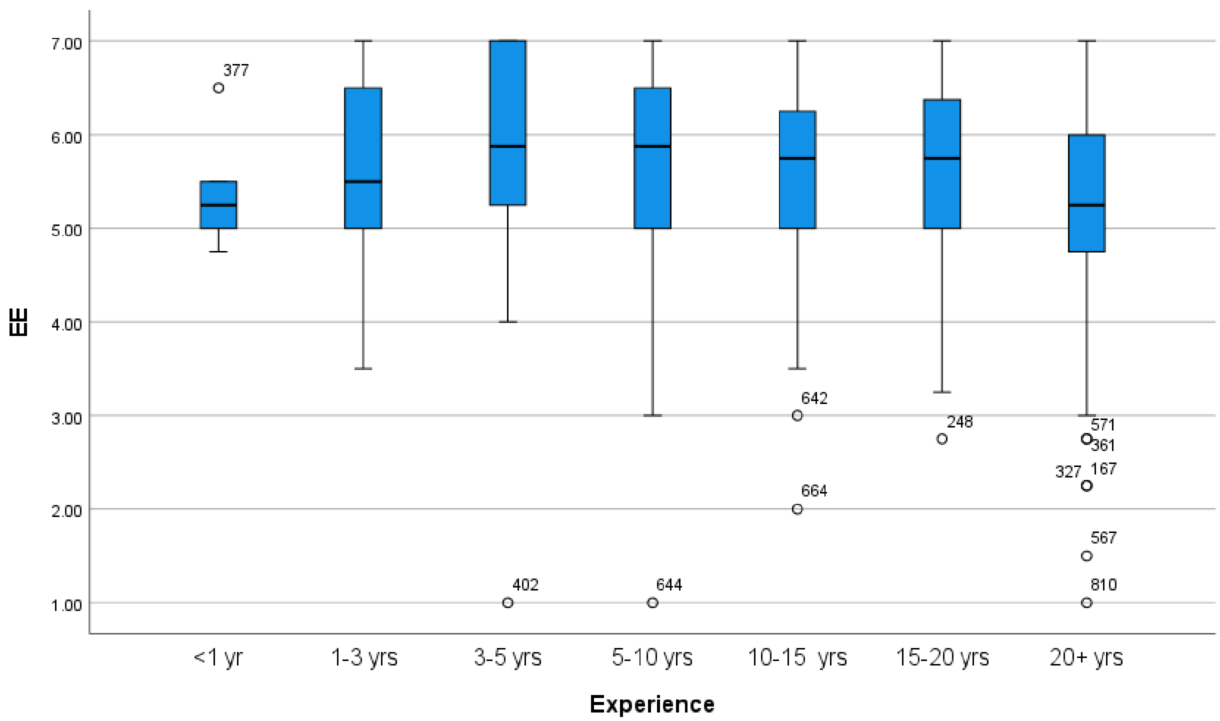
5-10 yrs
10-15 yrs
15-20 yrs
20+ yrs
Experience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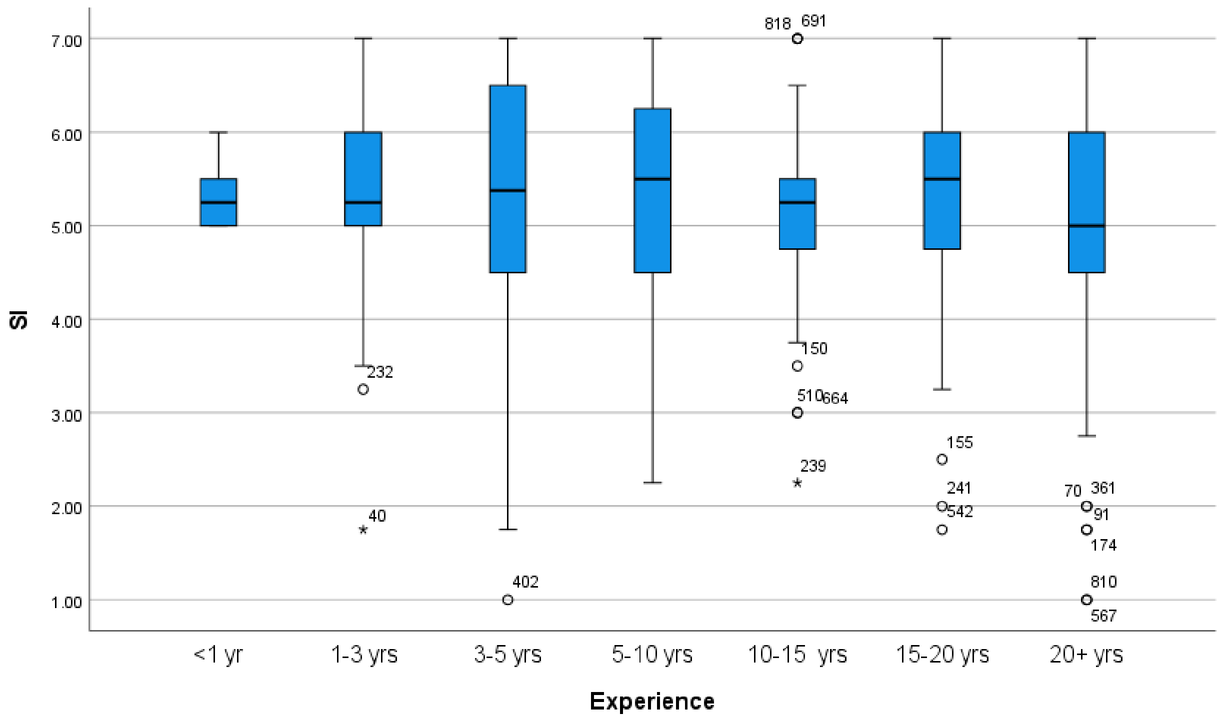
3-5 yrs
5-10 yrs
10-15 yrs
15-20 yrs
20+ yrs
Experience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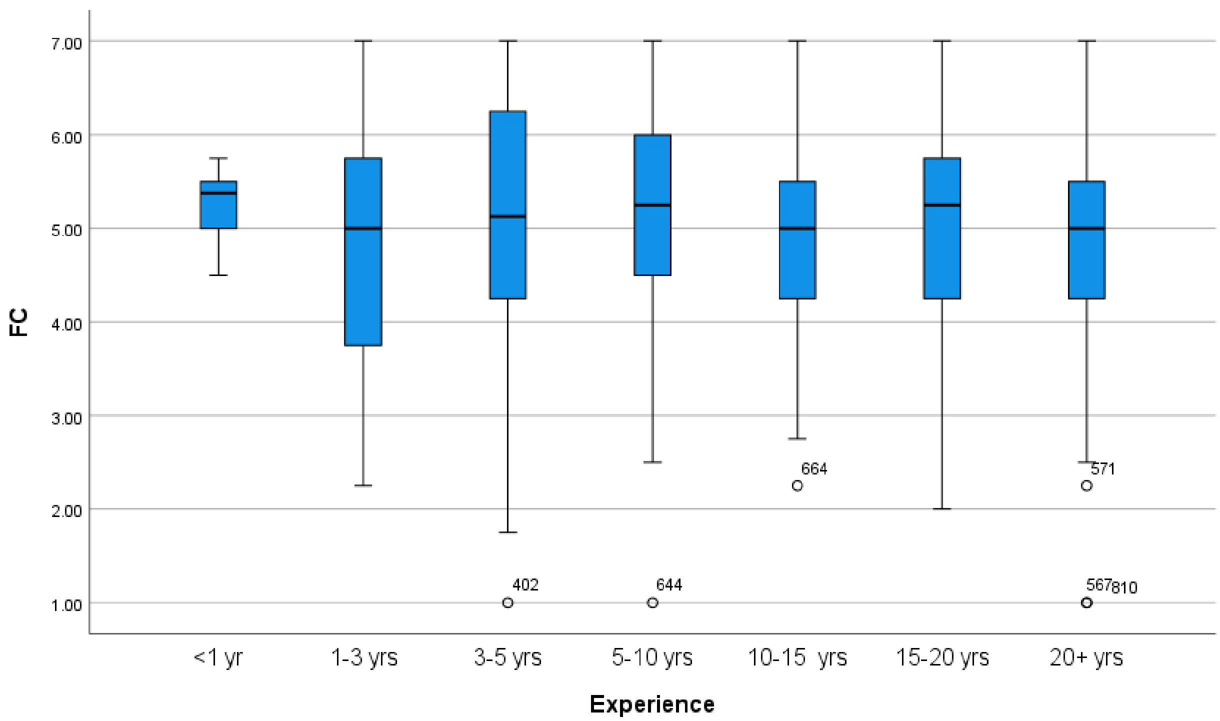
15-20 yrs
20+ yrs
Experience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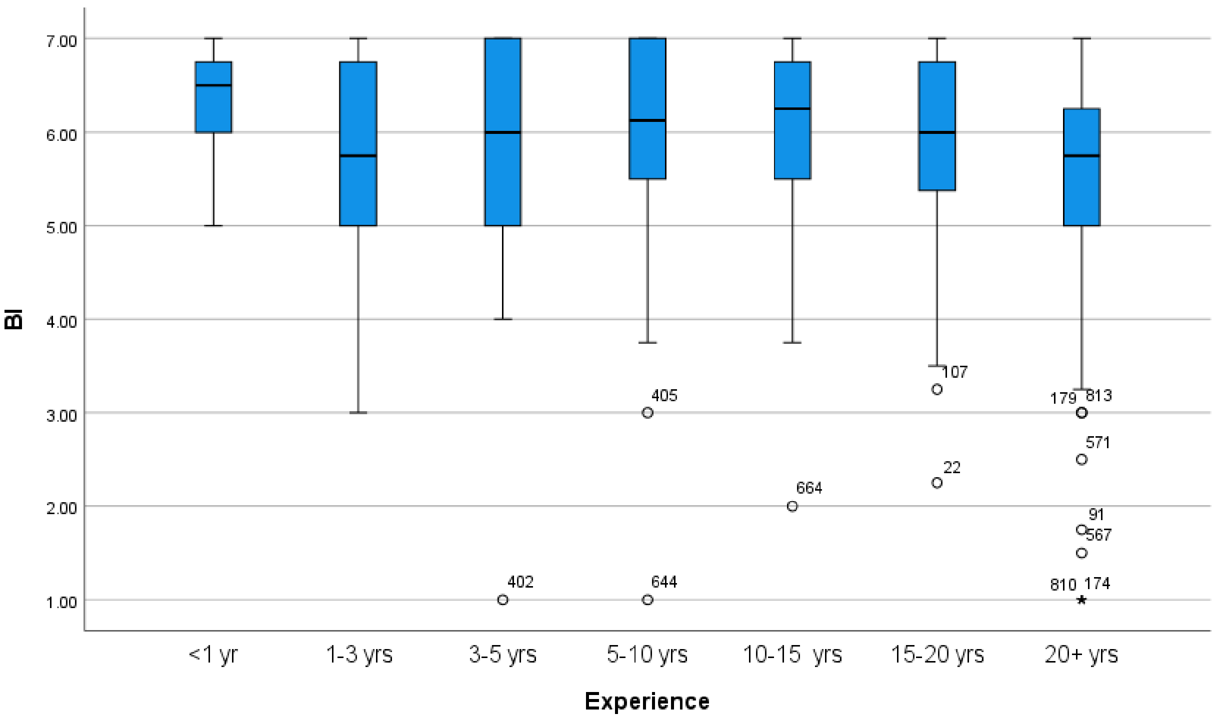
20+ yrs
Experience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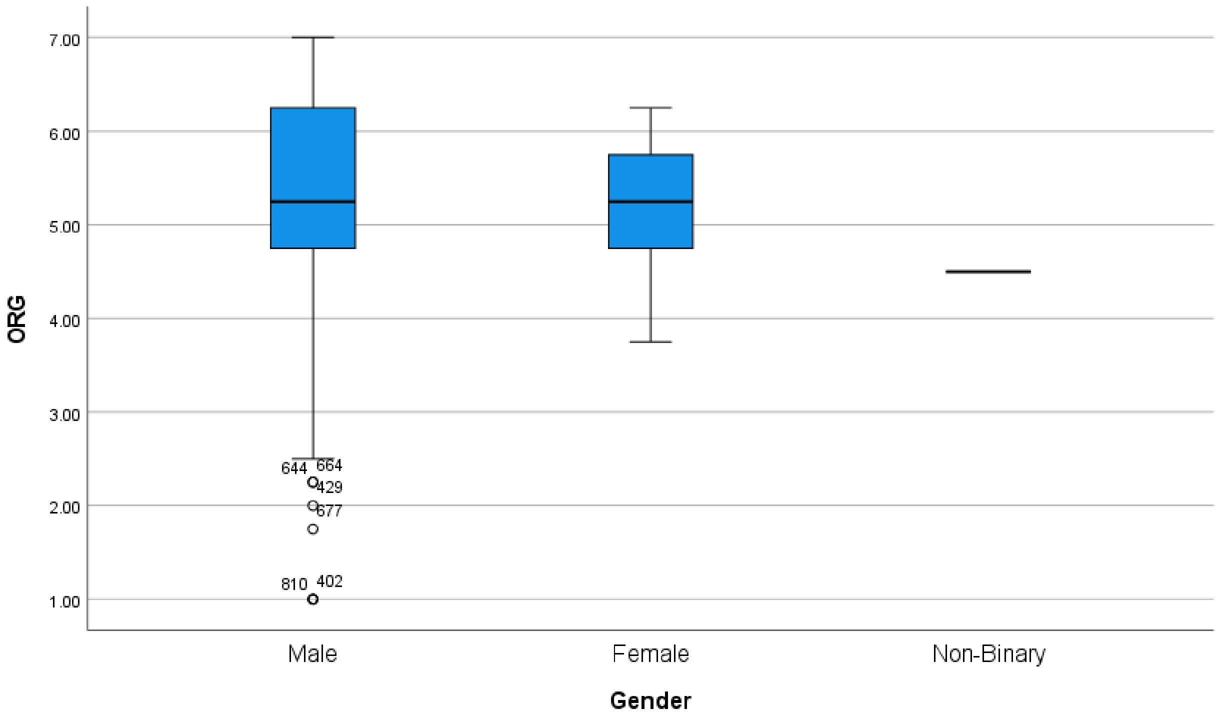
<1 yr
1-3 yrs
3-5 yrs
5-10 yrs
10-15 yrs
15-20 yrs
20+ yrs
Experience

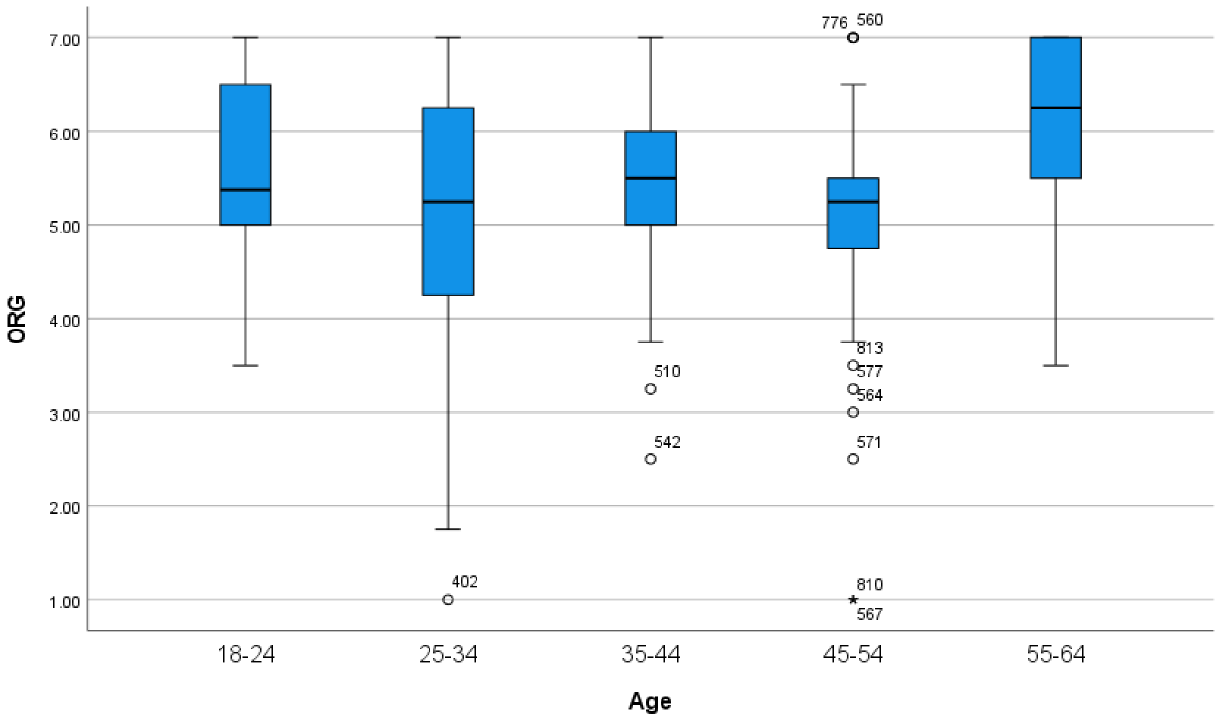
Gender
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Gender	N	Percent	N	Percent	N	Percent
ORG	Male	312	42.7%	418	57.3%	730	100.0%
	Female	28	31.8%	60	68.2%	88	100.0%
	Non-Binary	2	50.0%	2	50.0%	4	100.0%



Age
Case Processing Summary

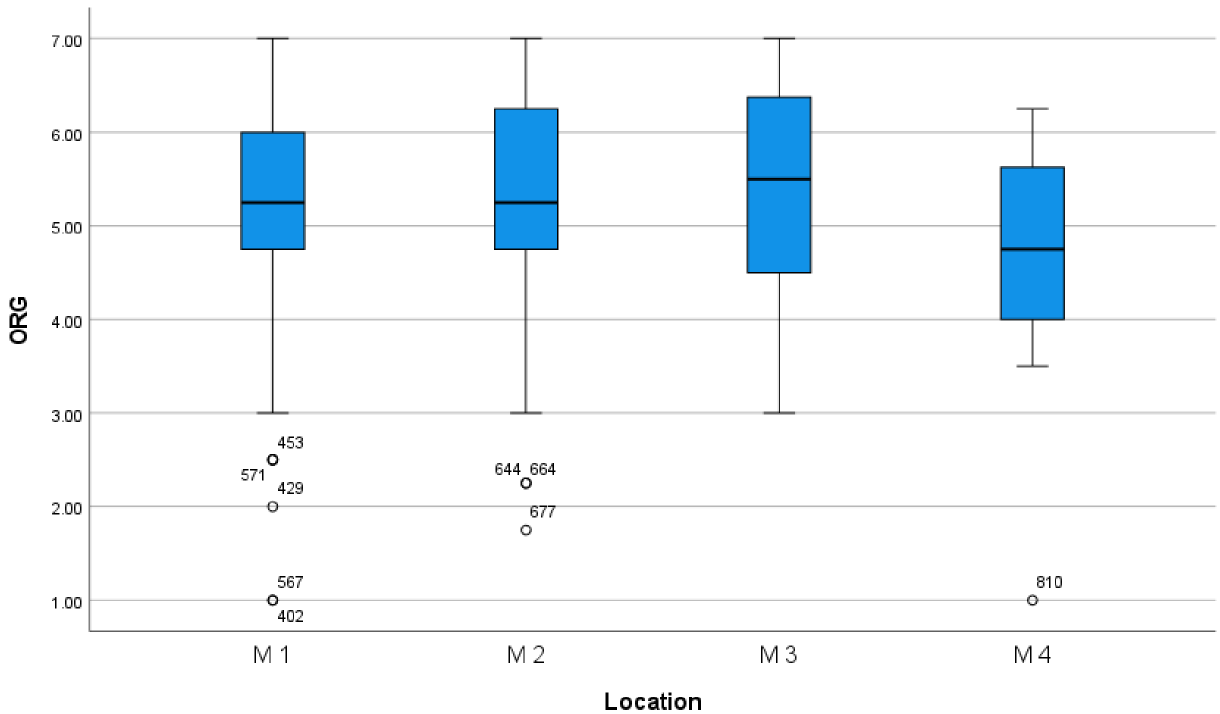
		Cases					
		Valid		Missing		Total	
	Age	N	Percent	N	Percent	N	Percent
ORG	18-24	20	62.5%	12	37.5%	32	100.0%
	25-34	141	57.1%	106	42.9%	247	100.0%
	35-44	103	43.5%	134	56.5%	237	100.0%
	45-54	67	30.6%	152	69.4%	219	100.0%
	55-64	11	13.6%	70	86.4%	81	100.0%



Location

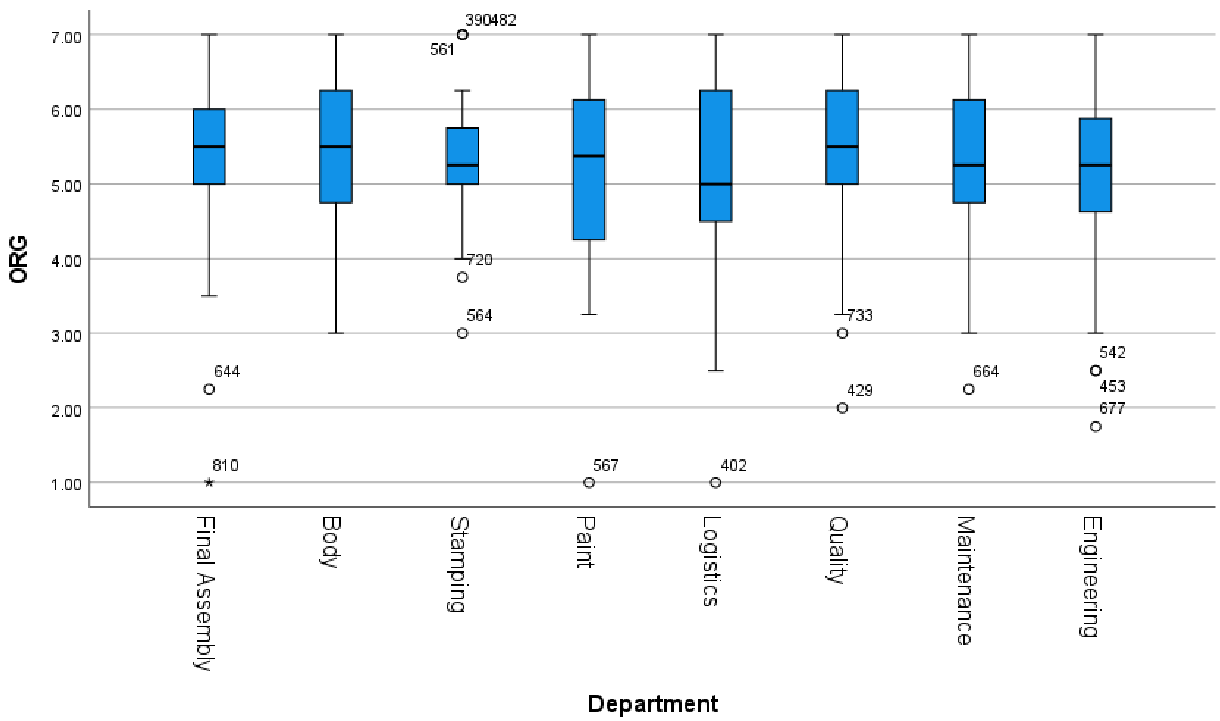
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Location	N	Percent	N	Percent	N	Percent
ORG	M 1	206	76.0%	65	24.0%	271	100.0%
	M 2	73	83.0%	15	17.0%	88	100.0%
	M 3	51	69.9%	22	30.1%	73	100.0%
	M 4	12	57.1%	9	42.9%	21	100.0%



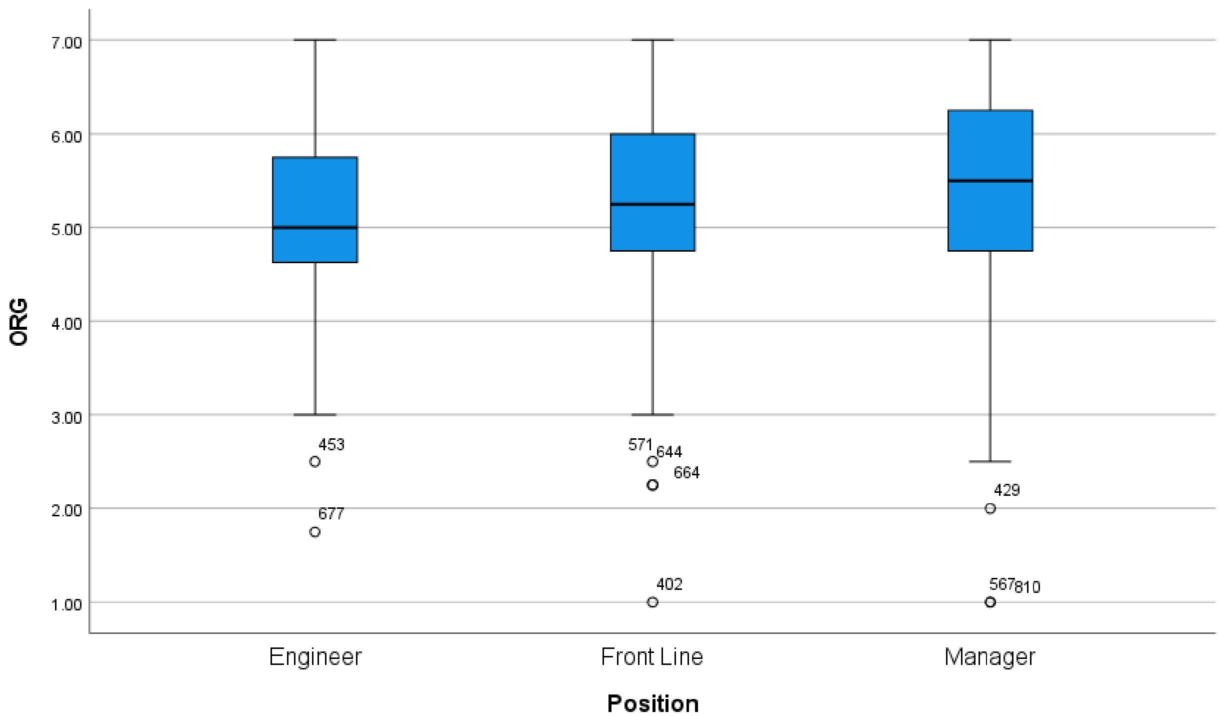
Department
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Department	N	Percent	N	Percent	N	Percent
ORG	Final Assembly	29	31.2%	64	68.8%	93	100.0%
	Body	33	48.5%	35	51.5%	68	100.0%
	Stamping	17	54.8%	14	45.2%	31	100.0%
	Paint	20	41.7%	28	58.3%	48	100.0%
	Logistics	46	56.8%	35	43.2%	81	100.0%
	Quality	45	54.9%	37	45.1%	82	100.0%
	Maintenance	80	63.5%	46	36.5%	126	100.0%
	Engineering	72	33.0%	146	67.0%	218	100.0%



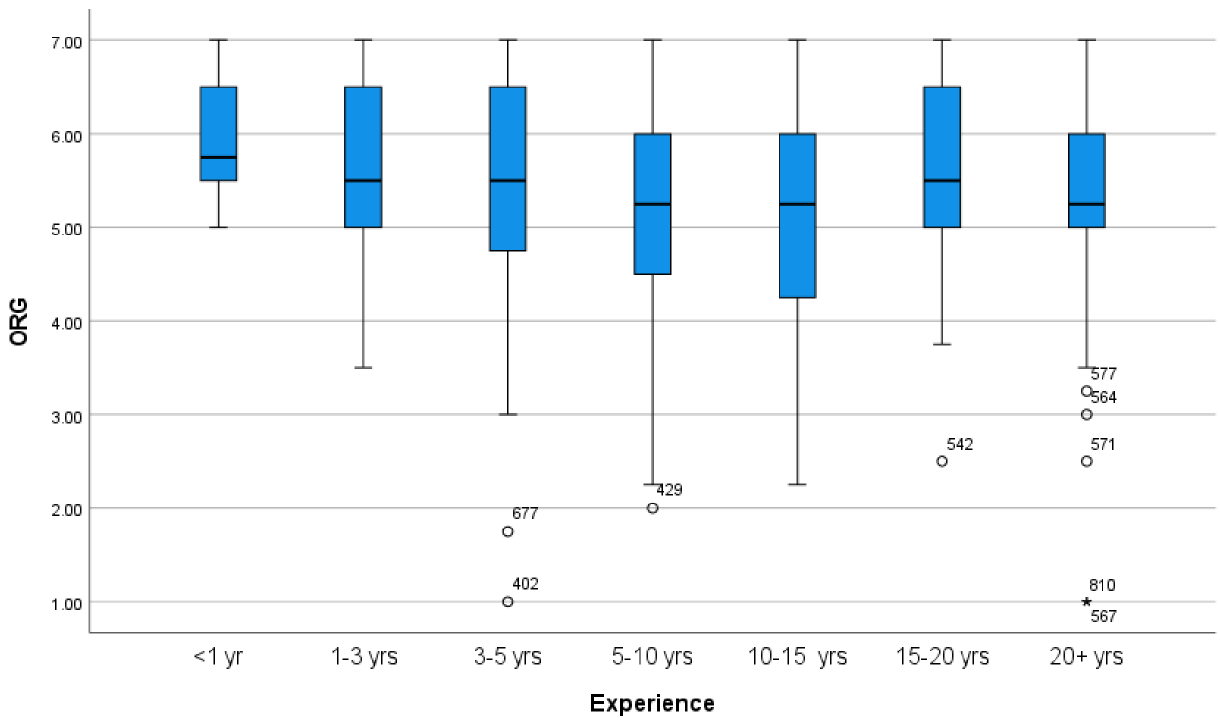
Job Role
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Position	N	Percent	N	Percent	N	Percent
ORG	Engineer	63	28.9%	155	71.1%	218	100.0%
	Front Line	140	56.5%	108	43.5%	248	100.0%
	Manager	139	41.7%	194	58.3%	333	100.0%



Experience
Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Experience	N	Percent	N	Percent	N	Percent
ORG	<1 yr	5	83.3%	1	16.7%	6	100.0%
	1-3 yrs	21	51.2%	20	48.8%	41	100.0%
	3-5 yrs	38	71.7%	15	28.3%	53	100.0%
	5-10 yrs	90	54.9%	74	45.1%	164	100.0%
	10-15 yrs	58	61.1%	37	38.9%	95	100.0%
	15-20 yrs	36	28.8%	89	71.2%	125	100.0%
	20+ yrs	94	38.7%	149	61.3%	243	100.0%



Region

Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Region	N	Percent	N	Percent	N	Percent
ORG	Mexico	342	74.7%	116	25.3%	458	100.0%