IMPLEMENTING INDUSTRY 4.0: A STUDY OF SOCIO-TECHNICAL READINESS

AMONG MANUFACTURERS IN MINNESOTA AND NORTH DAKOTA

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Title

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The Supervisory Committee certifies that this *disquisition* complies with North Dakota

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ABSTRACT

The implementation of Industry 4.0 has become increasingly prevalent in the manufacturing industry since its inception. With the introduction of these newer technologies, changes in personnel and organizational structures occur. The purposeful joint optimization of social and technical factors of organizations is imperative to the successful adoption of Industry 4.0. Thus, the socio-technical system theory addresses a holistic design of human, technology, and organization subsystems of the manufacturing process and their interdependencies.

This dissertation investigates the progress made towards implementing Industry 4.0 by small, medium, and large manufacturers in Minnesota and North Dakota. The outcomes of two surveys conducted among a group in Minnesota and North Dakota are analyzed and the results are compared to national and international data. This research identifies potential challenges, as well as, advantages in the current socio-economic landscape for manufacturers that may be either impeding or encouraging the development of a competitive and sustainable manufacturing business. As well, the implementation of flexible work arrangements in the modern work environment has increased in recent years. The first survey posed questions based on a sociotechnical theory framework, Industry 4.0, and productivity outcomes. Insights were provided as to how regional manufacturers were utilizing the socio-technical design framework to integrate Industry 4.0 into the organizational design and extract value, such as increased productivity. The joint optimization of social and technical factors within an organization is necessary for the successful adoption of hybrid work environments. The outcomes of the second survey conducted among a group of small, medium, and large manufacturers in Minnesota and North Dakota were assessed the level of socio-technical readiness among regional manufacturers. The survey posed questions based on socio-technical design, digital maturity, organizational learning, responsible

autonomy, leadership, communication strategies, and reduced work week schedules. Insights were provided as to how these critical factors support sustainability initiatives, such as reduced work week schedules. As a result of the surveys, a socio-technical strengths, weaknesses, opportunities, and threats (SWOT) analysis framework to complete was proposed to guide the organization through the industry 4.0 implementation process, assess opportunities for the reduction of work hours, and facilitate the strategic enterprise-wide buy-in from employees and diverse stakeholders.

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DEDICATION

This dissertation is dedicated to my parents and family for their continuous encouragement and

support.

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1. INTRODUCTION

Estimates have placed the pace of internet use from online consumers by 2030 to be once every 18 seconds or 5000 times a day (Satyro et al., 2023). Consumers are driving greater demands for mass customization, which provides a significant incentive for manufacturers to implement Industry 4.0 technologies (Dossou et al., 2022). In 2011 the manufacturing industry in Germany announced its focus on Industry 4.0 to meet these evolving market demands and to improve production accuracy, reduce inventory, operating and human resource costs, and further investment opportunities (Setyaningsih et al., 2020).

The academic literature in the field of Industry 4.0 studies focuses on increasing organizational flexibility and resilience, which may be reached through decentralization and realtime logistics. As well, sustainability, consumer empowerment, and product and service customization were studied (Pucheanu et al., 2022). Industry 4.0 requires the adequate appropriation of resources to implement successfully. The socio-technical systems theory can assist with the reduction of the reliance on resources, as well as, the adequate allocation of resources through its readiness assessment techniques, which directly supports this endeavor. (Setyaningsih et al., 2020). Assessment models, such as the socio-technical readiness surveys, that are conducted in this research, are essential to Industry 4.0 implementation (Haring et al., 2023).

Additional focuses on new application areas of socio-technical theory, such as technology platforms and the platform economy are conducted. As well, gaps in socio-technical research in predictive work have been identified (Abbas & Michael, 2022). Research topics on sustainability are also increasingly important. Socio-technical dimensions such as people, organization, and technology are directly correlated in the research to measures of critical success factors for developing sustainability (Koldewey et al., 2022).

Business size matters in discussions of Industry 4.0 adoption due to the historically limited financial resources of smaller enterprises (Sievers et al., 2021). Additional reasons for delaying Industry 4.0 integration may be a lack of employee knowledge, a hierarchical organizational structure and culture, and inadequate procedures to guide implementation in a volatile, uncertain, complex, and ambiguous digital transformation process (Gabriel et al., 2021).

The use of Industry 4.0 is becoming increasingly prevalent among industries, such as manufacturing. Industry 4.0 integration's goals are to support more autonomous, decentralized, and responsible work teams to move toward customized production (Bastos et al., 2022). The four design principles of Industry 4.0 are connectivity, decentralized decision-making, information transparency, and technical assistance (Yildizbasi and Unlu, 2019). Industry 4.0 connects the physical and digital assets to create an artificially intelligent and decentralized organization (Guertler et al., 2023). The Internet of Things, cloud computing, and big data and analytics create the opportunity to capture and leverage real-time data from products, processes, services, and people. These multi-faceted innovations will develop long-term solutions that create stronger sustainability, human resources, and supply chains (Tortorella et al., 2022).

Additionally, the vertical, horizontal, and end-to-end integration methodologies of these new enabling technologies will aid in the implementation of Industry 4.0 systems (Salunkhe & Berglund, 2022). Vertical integration is implemented using software tools, such as enterprise resource planning and manufacturing execution system, to influence planning and manufacturing within the organization. This technology implementation may shift the hierarchical structure of an organization. The horizontal integration supports the flow of material and information between the manufacturer and the supply chain network (Yildizbasi and Unlu, 2020). The end-to-end solutions create greater opportunities for customization (Sivananda et al., 2021). Also, vertical

integration focuses on the areas of information processing, products, and equipment. Horizontal integration emphasizes the connectivity to strategic partners and information flow (Chonsawat & Sopadang, 2020).

Modular production, service orientation, virtual applications, real-time capabilities, interoperability, decentralized systems and virtual applications enable the implementation of Industry 4.0 (Satyro et al., 2023). Modularity is defined as the ability for a manufacturer to instill flexible assembly through a variety of configurations to develop various products (Roy et al., 2023). Modularity, along with agility, flexibility, scalability, and interoperability synergies, aids in the digital transformation process (Haring et al., 2023).

Industry 4.0 technologies are critical to enhancing innovation and the competitive advantage of manufacturers in local and global markets through a combination of new digital technologies, products, and services (Sofic et al., 2022). Industry 4.0 is creating a more complex modern production system. The increased utilization of digital solutions generates advanced manufacturing data analytics (small data), predictive modelling, and real-time analytics to support decision-making. Yet, manufacturers are slow to adopt digital transformation strategies, which is evidenced in an overall less mature use of innovative technologies and are therefore predominantly in the earlier stages of Industry 4.0 (Clausen, 2023).

Socio-technical theory is an organizational theory that focuses on jointly optimizing the social and technical components of a work organization. Socio-technical theory was introduced by Trist and Bamford in 1951 as they studied the work-flow processes of coal miners. Sociotechnical theory defines employees as a resource to develop (Pasmore et al., 2019). A trait of process maturity is where the employee is co-responsible for decision-making (Jalowiec & Wojtaszek, 2022). The theory details the social, technical, work organization, and design of

internal and external factors affecting the work environment. According to this theory, a business socially comprises employee engagement, employee development, knowledge, safety, personal interests, skills, and experience. The technical elements of businesses are described as operations, processes, tools, facilities, equipment, inventory, maintenance, and information flow. The work aspects involve policies, rules, procedures, instructions, information flows, teams, employee shifts, training, planning, and integration. The design principles of goals, cyber-physical connection, information, transparency, decentralized decision-making, and employee input contribute to the joint optimization of the social and technical elements of an organization. Market demands, production processes, employee condition improvement, financial/economic environment, regulatory environment, and customization represent environmental work elements (Macron et al., 2021).

Socio-technical system design supports sustainable development within organizations. Additionally, Industry 4.0 technologies are proving to support environmental sustainability goals, as manufacturing processes are completed with improved efficiency while relying on fewer resources for total production (Javaid et al., 2022). Industry 4.0 tools are enabling technologies to assist small, medium, and large businesses with the sharing of information and collaboration between individuals, accessibility and security of the flow of data, mobility of work times and locations, and improved productivity and working conditions for employees (Cimini & Cavalieri, 2022). These newer technologies are providing improved production processes, increased productivity, reducing reliance on resources, decreasing costs, improving quality, and creating a more transparent and profitable organization (Cerne et al, 2023). Industry 4.0 serves well an organizational design that requires agility to address continuous, complex, and non-linear change. Reasons for implementing Industry 4.0 are consumer demands for

customization, supply chain complexity, and globally dispersed production, competition, and labor challenges (Zhou et al., 2022)(Biglardi et al., 2023). The Oxford English Dictionary defines agility as "the ability to think quickly and in an intelligent way" (Szabo, P. et al., 2023). An agile organization responds immediately to unexpected change to adapt as demands shift. Established processes that add value in dynamic business environments are known as strategic agility. Agile organizations also have the characteristics of reconfigurability within manufacturing systems that facilitates the adoption of Industry 4.0, which leads to increased productivity. Factors that directly impact the level of SME agility are production system structure, product decomposition, technologies leveraged, and business plan (Bouchard et al, 2023).

Although non-linear and non-transitive, socio-technical design is synchronous and interactive in developing value (Kurtz et al, 2023). In jointly optimizing Industry 4.0 with sociotechnical work design, observations of increased performance with the technical system and Operator 4.0, job satisfaction, increased safety, a collaborative economy and improved economic outcomes have been reported. The Operator 4.0 viewpoint focuses on the overall employee's capacity (De Assis et al, 2022). (Margherita & Braccini, 2021). Strong technology adoption rates are also indicated with the use of socio-technical theory (Macron et al., 2021). A more recent trend focuses on the conversion to human-machine co-working and is referred to as Industry 5.0, where humans are both originators and consumers of knowledge along with machines. The onset of the Industry 5.0 smart factory is based on the needs and skills of the workers, rather than the utility of the technology (Peruzzini et al, 2023). These synergistic human-cyber relationships integrate socio-democratic and ethical factors, where human intelligence partnered with cognitive computing create value-added products and services (Bednar and Welch, 2020).

Human-centered design considers cognitive psychology, industrial design, information processing graphics, human factors, and ergonomics (Ngoc et al., 2021). There are three types of ergonomics: physical, cognitive, and organizational. Physical ergonomics focuses on the employee's movement, safety, and health. Cognitive ergonomics focuses on performance, decision-making, training, and cyber-physical interactions. Organizational ergonomics focuses on schedules, processes, communication, collaboration, and structures (e.g. flat or hierarchical organization) (Zizic et al., 2022).

Smart technologies are innately socio-technical connecting the production process and products to issues of environmental, social and economic sustainability. New research is being conducted on both user and worker perspective of smart technology, where privacy, autonomy, and the dehumanization of interactions is observed. Gray areas aligned with the human-AI interaction are language processing, social roots, cyber-physical systems, virtual reality, and augmented reality (Ngoc et al., 2021). The human-centered systemwide perspective considers the three main areas of human-centered industrial engineering, human-centered modelling, and human-centered management, which correlate directly to the socio-technical system design theory (Sgarbossa et al., 2020). The goal of human-centered design is to create decentralized organizational techniques, which simultaneously serves as a catalyst to flatten hierarchical structures (Dregger et al., 2016).

In this paper, a socio-technical framework provided by Davis et al. is used to assess the interdependent nature of work systems that support both predictive work and design (Davis et al., 2014). The socio-technical framework consists of three external factors and six internal factors. The external factors have been identified to influence the connections between technological and social aspects, including regulation, financial circumstances, and stakeholders. The internal

factors of organizations can be categorized into three technological aspects: technology, infrastructure, process, and three social aspects, namely goals, people, and culture. This analysis of technical, organizational, and employee-related factors is holistic and offers insights into the correlations among the five socio-technical constructs. These constructs are data gathering, analysis and interpretation, summarization, testing, and iterating and amending. These sociotechnical constructs are viewed through the lens of Industry 4.0 integration, as well as, productivity outcomes among small, medium, and large manufacturers in North Dakota and Minnesota (Davis et al., 2014).

The existing literature gap encouraged the focus of this study to assess the socio-technical dimensions of manufacturers in North Dakota and Minnesota in the context of Industry 4.0 adoption. According to the National Association of Manufacturers, as of 2019, there were 624 manufacturing firms in North Dakota. In North Dakota as of 2021 manufacturers employed 27,000. There are 6387 manufacturing firms in Minnesota that account for 320,000 employees (National Association of Manufacturers, 2023). These manufacturing firms employ 6.32% of nonfarm workers in North Dakota and 11.08% of non-farm workers in Minnesota as of 2021. Additionally, due to North Dakota and Minnesota's low unemployment rates of 2% and 2.9%, respectively, as of June 2023, the assessment is also imperative of the integration of human factors through the implementation of the socio-technical theory framework to support sustainability plans (National Association of Manufacturers, 2023). The study is especially needed to assess regional competitiveness of manufacturing firms in the Industry 4.0 context using the lens of socio-technical design, which is described as the joint optimization of social and technical factors, is self-managing to embody resourcefulness, and where the employees are multi-skilled to ensure successful performance in dynamic business environments (Mitki et al., 2019).

Flexible work arrangements are also of increasing interest to the present-day workforce. In 2022, 34 percent of employed persons did some or all of their work at home and 69 percent of employed persons did some or all of their work at their workplace. On average, those who worked at home did so for 5.4 hours on days they worked and those who worked at their workplace did so for 7.9 hours. (U.S. Bureau of Labor Statistics, Accessed on 1 October 2023).

The state of North Dakota's Economic Development Foundation developed a Strategic Plan for 2017-2025, which includes a strategic vision for advanced manufacturing by assessing the critical area of entrepreneurship and innovation. This report outlines the strategic responsibilities of the state to successfully implement a vision for continued growth. These outlined goals include continuing to invest in university-based research and development conducted with the private sector that engages North Dakota in emerging technologies and work to fast-track commercialization, promote export trade, and continue investing in statewide talent strategies that address education, training recruitment and retention to support long-term sustainability goals (commerce.nd.gov, 09/25/23). Alternately, Enterprise Minnesota is a participant of the U.S. Department of Commerce's Manufacturing Extension Program and has conducted surveys illustrating several key indicators of the current status of manufacturers in Minnesota. When surveyed Minnesota manufacturing firms indicated that increasing productivity, developing company managers and leaders, effective strategic planning and implementation, and implementing and using automation were within the top ten drivers of the company's future growth (enterpriseminnesota.org, 9/26/2023). Furthermore, on a national level the United States commenced the Advanced Manufacturing Partnership and the National Network for Manufacturing Innovation in 2014 to foster continued economic growth (Trehan & Machhan, 2022).

The objective of the research is to evaluate the technical and social factors impacting modern manufacturers' ability to work in new and meaningful ways, such as through reduced work week schedules resulting from developing a culture of organizational learning, responsible autonomy, bottom-up problem solving, and promoting productivity and innovation. Reports indicate that reduced work week schedules are successfully implemented in Germany and Austria, as well as several other countries, such as in New Zealand and Japan. The overall belief is that reduced work week schedules support sustainability goals, such as employee safety, wellbeing, and job satisfaction (Gaitlin-Keener & Lunsford, 2020). Furthermore, a socio-technical analysis framework will be introduced to address the strengths, weaknesses, opportunities, and threats hindering the joint optimization of social and technical elements throughout the enterprise.

This study is grounded in socio-technical theory as described by Davis et al. where the joint optimization of technical components, such as technology, processes and infrastructure and social components of people, goals, and culture operate interdependently and efficiently (Davis et al., 2014). When either the social or technical component is unattended a less than optimal outcome is observed. This study contributes to the literature on socio-technical systems theory by measuring the regional impact of socio-technical design among small, medium enterprises (SMEs), as well as large manufacturers.

1.1. Research Rationale

Organizations may be described as systems with behaviors, structures, and functions (Doussou et al., 2022). This paper seeks to assess the socio-technical readiness of manufacturers in Minnesota and North Dakota to both integrate Industry 4.0 and instill a reduced work week goal within their organizations.

1.1.1. Research Questions

The objective of the research questions is to glean insights into the current level of sociotechnical design that is integrated within an organization. This study focuses on socio-technical design framework constructs that can facilitate the successful adoption of Industry 4.0, as well as predict the dependent variables of increased productivity and reduced work week schedules. A hypothetical model is also presented to illustrate and test the correlation between socio-technical constructs and the current status of an organization's work design. The following six research questions pertain to the socio-technical readiness of small, medium, and large manufacturers in Minnesota and North Dakota in the Industry 4.0 implementation process.

- 1. How applicable are socio-technical design principles in the Industry 4.0 context among North Dakota and Minnesota manufacturers?
- 2. Is there a positive correlation between Industry 4.0 and increased productivity among manufacturers in Minnesota and North Dakota?
- 3. Is there a positive correlation between socio-technical design principles and increased productivity?
- 4. Will organizational learning have a significantly positive correlation to achieving a reduced daily work hour goal?
- 5. Will responsible autonomy have a significantly positive correlation to the promotion of productivity and innovation?
- 6. Will responsible autonomy have a significantly positive correlation to organizational learning among regional manufacturers?

2. LITERATURE REVIEW

The structure of work, technology, and design practices are ever changing, informing the use of socio-technical principles and applications. The work organization operates with goals and metrics and the aid of people of varying skills and attitudes, using a range of technologies and tools, leveraging infrastructures, holding specific cultural orientations, and following a set of processes. As mentioned previously, a work organization is a system that operates within the external environment and is impacted by regulatory frameworks, stakeholders, and the economic and financial environment. The current status of an older workforce dated industrial facilities, and environmental concerns in many areas of the world calls for the digital transformation of the manufacturing sector that is informed by a human-centered design (Gales et al., 2022).

The socio-technical analysis offered by Davis et al. outlined that the socio-technical framework includes the constructs of data gathering, analysis and interpretation, summarization, testing, and iterating and amending within the six dimensions of people, infrastructure, technologies, culture, processes, and goals. This socio-technical framework assists with predictive work and is significant in designing and overseeing project implementation. The themes of enduser engagement and team-based approaches promote sustainability (Davis et al., 2014). Badham et al. provided five descriptors for socio-technical systems as systems having independent parts, being adaptive, holding both social and technical subsystems, having multiple pathways for obtaining objectives, and overall system performance occurring through joint optimization. Cherns described nine socio-technical principles as: "(i) Compatibility: the design process must align with its objectives. (ii) Minimum critical specification: social groups should have clear objectives, but they should decide how to achieve them. (iii) Socio-technical criteria: deviations from expected norms and standards should be eliminated or controlled. (iv) Multifunctionality

principle: groups should facilitate the exchange of knowledge and experiences. All groups should learn from each other. (vi) Information should be transmitted to where it is needed for action. (vii) Supporting congruence: social support systems that reinforce desired behavior should be designed. (viii) Design and human values: quality work requires opportunities that lead to a desirable future. (ix) Incomplete establishes that design is an iterative process that never stops." (Agote-Garrido et al., 2023)(Challenger and Clegg, 2011).

Socio-technical theory is connected to ethical factors, as well as technical-economic factors (Yue et al., 2020). Socio-technical systems are recognized by the U.N. as imperative to Sustainable Development Goals (Rojas et al., 2022). The socio-technical theory provides insights to support an organization's need for both social and technical organizational standards to ensure the successful interoperability of Industry 4.0 technologies with human factors. This method creates new business models for new communication and information technology implementation through instituting a high coordination effort (Orzes et al, 2018). Implementing organizational development involves diverse stakeholder participation, is organizationally-led, improves skills, communication, introspection of leadership and culture, and encourages continuous improvement (Blake and Mouton, 2001).

Important concepts to Socio-technical theory are responsible autonomy, autonomous groups, self-regulation, and participant design as part of the digitization process (Thomassen et al., 2017). Socio-technical systems design includes incompletion, in which continuous improvement is fostered (Davis et al., 2014). Another manner of conceptualizing incompletion is as continuous "design-in-use" where insights are collected from a variety of stakeholders, such as workers (Gales et al., 2022). The framework for applying socio-technical design may differ based on variables such as the size of the business. Participative design is a democratic process of

integrating the norms and values within the organizational culture into a system's design. The employee is the participant and provides direct input regarding the design, length of participation in the design process, the significance of the input, and the level of decision-making (Ahmad et al., 2022). The three principles guiding socio-technical design per Bastidas et al. are trustworthiness and trust among stakeholders, technical design correlations with organizational context, and access to resources and solutions that directly align with organizational culture. Designing socio-technical work organizations also considers the assessment of competencies, developing cross-disciplinary leaders and defining the tasks of the Industry 4.0 technologies (Bastidas et al., 2023). Furthermore, the socio-technical skill of team fluidity is essential for successfully implementing Industry 4.0 (Nayernia et al., 2022). Additionally, a study conducted by Marcon et al. found that joint optimization of the social and technical aspects will lead to greater technology adoption rates (Marcon et al., 2021).

Socio-technical attributes encourage team responsibility (Kaminiski, 2022). Organizational learning is achieved through the empowerment of employees, creating responsible autonomy observed at both the individual and team levels. Responsibility is the foundation for control, which is found in skill discretion and task authority (Enehaug, 2017). Sharing autonomy is an operational concept that sustains the dynamic relationship between individual autonomy and collective behavior (Heininger et al., 2023).

2.1. Industry 4.0 Adoption Differences Among Small, Medium, and Large Manufacturers

A prerequisite to ensuring the entire supply chain is operating efficiently to meet changing consumer demands is through the integration of the information and communication technologies of Industry 4.0 (Pech and Vrchota, 2020). The key design principles of Industry 4.0 are interoperability, predictability, real-time data analysis, system intelligence, and flexibility

(Nayernia et al., 2022) (Peruzzini et al., 2023). The cyber-physical information flow processes are information acquisition, information analysis, decision selection, decision implementation, and innovation (Heininger et al., 2023). Studies have shown that small and medium-sized enterprises resist sharing data within the supply chain due to data security and negotiation power (Nayernia et al., 2022). Common descriptors of small businesses are low-profit margins, limited training and staff development, informal quality control, narrow customer base, lack of negotiating power over suppliers, lack of long-term plans and strategies, and limited resources and capacities (Minshull et al., 2022). Competitive disadvantages that SMEs have in comparison to large enterprises are a lack of technological infrastructure, lack of advanced manufacturing technologies, lack of management knowledgeable of Industry 4.0, and lack of standard procedures. A recent study by Pech and Vrchota reported that small and medium-sized enterprises utilize technologies commonly for the purpose of analysis, collecting data, and cloud storage (Pech and Vrchota, 2020).

The relative advantages provided by Industry 4.0, the compatibility of manufacturing equipment and processes to intended technology use to drive collaboration and integration, top management support, and competitive pressure are key selling points in support of its adoption (Shahzad et al., 2023). The presence of a digital infrastructure and the personnel's level of knowledge to process and understand data are instrumental to Industry 4.0 adoption as well (Khourshed et al., 2023).

There are estimates that 400 million small and medium-sized enterprises exist worldwide (Haring et al., 2023). Small, medium, and large businesses choose to adopt Industry 4.0 for a variety of reasons. These reasons include increased productivity, customized software, increased customer care, and reduced labor requirements. Small, medium and micro-sized businesses vary

among the multitude of socio-economic contexts offered throughout the world. Waste reduction and increased productivity may be observed by increasing productivity through tools, such as Industry 4.0 (Qureshi et al., 2023). Often the Industry 4.0 integration plans are focused on production processes without regard to the entire work system and resource connectivity (Cerne et al., 2023). Businesses located in rural markets are typically smaller and have a higher concentration of solopreneur and micro-businesses (Jones et al., 2020). According to a Price Waterhouse Cooper report, the Industry 4.0 integration leads to a greater than 10% outcome in both the improvement in efficiency and a reduction in operational expenses (Bag et al., 2021). As well, industrial organizations that undergo a digital transformation may be more resilient to global crises (Neuhuttler et al., 2023).

McDermott et al. conducted a study of small, medium, and micro enterprises in the west of Ireland in 2022. The popular tools indicated to be helpful in this study by survey respondents were automation, smart processes, automated inspection, and cloud computing. The aims for adopting Industry 4.0 within small, medium, and micro enterprises were improved customer experience, reduced costs, improved long-term outlook for the business, improved product and service quality, increased profits, and increased capacity (McDermott et al., 2022). Automation may address both cognitive and manual activities, such as manual work, manual control, control activities, judgment and decision making (Stern & Becker, 2019).

The study also found that having the right equipment or software solution, having knowledgeable employees, having consultancy support, and having an adequate budget were critical success factors. A factor that the study considered as indicating a lack of Industry 4.0 adoption was the absence of leadership vision tethered to innovation through the use of new technologies (McDermott et al., 2023).

Obstacles may exist to adopting Industry 4.0, such as increased unemployment generation, data vulnerability, and challenges to device interconnection. Short-term risks to adopting new technologies include lack of employee expertise and short-term strategy (Kumar et al., 2021). A recent study conducted on the impacts of Industry 4.0 on industrial employment indicated as employees become familiar with digital transformation the less likely they are to expect substantial changes to workforce levels (Shuttleworth et al., 2022). An additional challenge may be a narrowly defined product portfolio in which to automate (Haring et al., 2023). Moeuf et al. reported that small and medium businesses have the potentially downside characteristics of local management, short-term strategy, lack of expertise, non-functional organization, limited resources, short-hierarchical lines, and lack of methods and procedures, which are challenges to adopting Industry 4.0. The study suggested simplifying the utility of a tool, such as a cloud computing platform for big data analysis to "offset a lack of technical competency, which is characteristic of the small and medium enterprise context". Another characteristic highlighted in the report by Moeuf et al. is that small and medium-sized businesses are innovative, entrepreneurial, and studious. Relaying the importance of data and orienting the small and medium-sized manufacturing operator toward leveraging data for regular operational use are catalysts for Industry 4.0 adoption and require the application of socio-technical theory design principles, as they imply continuous improvement processes. Implementing Industry 4.0 for these business sizes requires a leader specifically assigned to the Industry 4.0 project, who will engage in the necessary communication, have the necessary skills, factor in training versus consulting, and ensure the simplification of Industry 4.0 tools (Moeuf et al., 2021). The implementation of Industry 4.0 will require the organization to leverage Intrapreneurship to convey needed creative and innovative internal resources (Gupta & Jauhar, 2023). An agile process that is specific and

structured may align well with smaller enterprises and support aptitude building (Minshull et al., 2022). The employees are invaluable to contributing knowledge and problem-solving strategies, which allows for the integration of both human or worker data and machine data to create greater operational efficiencies (Peruzzini et al., 2023).

Managing the Industry 4.0 transformation in small and medium-sized enterprises (SMEs) differs compared to large enterprises. As mentioned above, small, and medium-sized enterprises tend to focus on short-term strategies and objectives. Flexibility is used when assessing new opportunities and challenges. Processes may not be in place compared to more organizationally mature large enterprises. Additionally, in comparison, large companies often strategize digital transformation throughout a larger architectural footprint. Systems are implemented to acquire vast amounts of data and initiate data valorization projects to leverage insights from the data acquired (Brodeur et al., 2022). The digital transformation in the large business focuses on business processes, integrating agility, improving work-balance, and increasing operational efficiencies overall (Cotrino et al., 2020). Success factors for small and medium-sized businesses that were highlighted by Brodeur et al. are aligning Industry 4.0 with business strategy, leadership, aligning along a hierarchical line, conducting a study prior to Industry 4.0 projects, managing communication, teamwork and team composition, employee training and knowledge management, organizational culture and change management, project management, and continuous improvement strategies. Continuous improvement strategies foster the development of employees' agility to learn new tools and processes (Brodeur et al., 2022). New technologies, such as AI are lacking in transparency and have abridged innovation timeframes leading evermore to the necessity of organizational flexibility (Neuhuttler et al., 2023). Organizations instilling the

strategy of continuous improvement are focused on both developing employee commitment and motivation, as well as operating more efficiently (Oudhis & Tenglad, 2020).

Knowledge management is defined as a continuous management of all types of knowledge and requires a comprehensive strategy inclusive of the elements of policy, implementation, monitoring, and evaluation. Knowledge management supports the organizational growth in the areas of skills and capacity building (Smuts & der Merwe, 2022). The production of organizational knowledge is heightened with the utilization of Industry 4.0 as it allows for opportunities to share, creating sustainable, safe and educated society (Satyro et al., 2023).

Throughout the process, self-evaluation translates into the capacity to execute and manage Industry 4.0 transformation, assessment of financial abilities, employees' expertise and experience in Industry 4.0 technologies and projects, internal project management and continuous improvement processes, resistance to change, and external resource availability. The company's management and key employees should be actively engaged in the evaluation process and communicate openly the results with the SME management (Brodeur et al., 2022). Industry 4.0 technological solutions will differ among small, medium, and large businesses. Implementation standards among groups will vary. Research has also shown that small and medium-sized businesses are often suppliers for larger businesses that are operating on Industry 4.0 principles. Digital transformation applied to logistics will realize efficiency gains along the entire supply chain (Tubis & Grzybowska, 2022).

Furthermore, the differences impacting Industry 4.0 implementation outlined between SMEs and large businesses are as follows. SMEs have barriers to accessing financial resources, advancing manufacturing technologies, research and development, standards, and strategic partnerships with universities and research institutions. Moreover, SMEs utilize software that is

tailored and therefore not standardized. Additionally, there are few knowledge carriers, and the leader is responsible for decision making. The SME organization is informal and simpler. The SMEs' human resources operate in a variety of domains. The SMEs' industry knowledge and experience are very specific. They are dependent on collaborative networks. Large businesses make decisions through boards of advisors and internal and external consultants. Large businesses exhibit contrary characteristics to SME traits (Tubis & Grzybowska, 2022). The deficit in resources hinders SMEs from participating in advanced value co-creation. Creative solutions exist for SMEs, such as mergers and acquisitions, inter-enterprise collaboration, and industry-university research cooperation, which represent open innovation ecosystem's value co-creation models (Li et al., 2022). Open innovation allows manufacturers to diversify and expand through connecting with innovative ideas, utilizing innovation inputs, and informing its supply chain to optimize its use (Madhavan et al., 2022). With regards to the open innovation ecosystem, this setting is characterized by its invitation to a diverse set of collaborators to provide insights and solutions to real organizational problems (Riquet et al., 2022). Open innovation allows consumers to participate in the design process of products, since the boundary between the consumers and designers works collaboratively to meet customization requirements (Yao et al., 2021). Open innovation also may expedite the innovation process while creating knowledge-sharing opportunities, decreasing costs, and targeting effectiveness. One study found the impetus for innovating in Industry 4.0 stemmed from the market force of substitution through the new market entries of content modifications with products and innovations (Kohnova & Salajova, 2023).
2.1.1. Reviewing The Nature of Small, Medium, and Large Manufacturers—The Changing Environment and Current Skills Gaps

The constructs of management, operations, and technology readiness directly correlate with the readiness of an organization to implement Industry 4.0 technologies (Ali et al., 2022). According to a recent study, Industry 4.0 is observed more with manufacturers in the B2B market than the B2C market (Kanovska and Bumberova, 2021). The nine fields of Industry 4.0 are cyberphysical systems, internet of things, big data, cyber security, cloud computing, additive manufacturing, advanced robotics, modelling and simulation, and augmented virtual reality (Peruzzini et al., 2023). These innovative technologies also include blockchain, digital platforms, autonomous vehicles, synthetic biology, artificial intelligence, machine learning, and analytics (Asiimwe & de Kock, 2023).

It is often cited as a barrier that small and medium-sized enterprises have limited skills that relate to the Industry 4.0 context. The socio-technical systems readiness survey assessments can assist with preparing the employees for the information that will need to be gathered, analyzed, and shared to utilize the newer communication and information technologies optimally (Setyaningsih et al, 2020). Employees will be required to develop new skillsets to manage the utilization of cyber-physical systems, the Internet of Things, cloud computing, enterprise resource planning, radio frequency identification, and social product development as key technologies in the manufacturing setting.

The Internet of Things is supported by cloud and edge computing, which allow process storing and interconnection (Trehan & Machhan, 2022). Cloud computing is very reliable, scalable and is offered at a low cost, which is a significant pathway for providing accessibility to the implementation of Industry 4.0 to small and medium-sized businesses (Liu et al., 2021). One

report indicated that cloud storage and computing are the most adopted technologies used by SMEs. Additional technologies and practices that are imperative for employees to understand are enterprise resource planning systems, manufacturing execution systems, real-time key performance indicators, and a knowledge management system. Observation and data collection are required activities to integrate Industry 4.0 (Roy et al., 2023).

2.1.2. Adopting Socio-Technical Design in the Industry 4.0 Context

The work organization operates with goals and metrics and the aid of people of varying skills and attitudes, using a range of technologies and tools, leveraging infrastructures, holding specific cultural orientations, and following a set of processes. A work organization is a system that operates within the external environment and is impacted by regulatory frameworks, stakeholders, and the economic and financial environment. The socio-technical framework assists with predictive work, such as determining productivity outcomes and labor scheduling, and is significant in designing and overseeing digital project implementation. The themes of end-user engagement and team-based approaches promote sustainability. Socio-technical system design involves the concept of incompletion, which requires continuous improvement (Davis et al., 2014). The concept of incompletion or an 'unfinished system' affords the organization the ability to pivot to address new short-term demands, as well as assess and advance the socio-technical system once new demands become new operational conditions (Maguire, 2014). Bastidas et al described the socio-technical design of tasks as a linear process of "planning tasks, testing tasks, embedding tasks, and enabling tasks", which relates to the operational process outlined by Davis et al (Bastidas et al., 2023). The digital transformation process allows manufacturing SMEs the ability to become more flexible, agile, and responsive to customer needs. Digital transformation can be integrated in design, planning, manufacturing, research and development, and service

activities (Dutta et al., 2021). The structure of work, technology, and design practices are ever changing, informing the use of socio-technical principles and applications.

Challenges to adopting Industry 4.0 among SMEs have been reported as a lack of employee knowledge and training capabilities on quality issues, financial constraints, cyber security, resistance to change, organizational culture, large data volume, integration of digital tools in infrastructure, data quality, and data ethics (Malin et al., 2023). Additional challenges to Industry 4.0 implementation have been reported as poor existing data, lack of employee skills, and lack of technological infrastructure. Manufacturers may also lack government support and be unclear of the economic benefits (Alsaadi, 2022). Smart or digital retrofitting has been a costeffective solution employed by SMEs to provide advantages to successfully adopting Industry 4.0. The practice requires the utilization of software, such as artificial intelligence, machine learning algorithms, neural networks, digital twins, cloud systems, and remote maintenance (Pietrangeli et al., 2023).

Cross training employees to understand skills from divisions outside their own strengthens internal capacities to conduct continuous research, analysis and decision making, which are integral skills to developing employee adaptability (Sony & Mekoth, 2022). As well, the type of digital maturity of an organization provides an indication of how innovative and responsive to customer requirements the SME is likely to be (Dutta et al., 2021). The level of organizational focus on social factors, such as training and management support also provides advantages to adopting Industry 4.0. Economic factors such as employee innovation and perceived usefulness also support Industry 4.0 adoption rates. The technical subsystem of holistic internal cooperation, effective use of knowledge, techniques, equipment, and facilities also support digital transformation (Zemlyak et al., 2022).

Project teams representing a diversity of stakeholders may work to ensure that human factors are integrated due to the team's specific work knowledge that will contribute to sociotechnical design (Choi et al., 2022). An iterative approach in developing cross-trained employees is commencing in a specific area within the organization and scaling across divisions. This allows the organization to cautiously build internal capabilities of employees to work with data and to interpret this successfully while quickly creating successful outcomes (Harland et al., 2022). The socio-technical theory emphasizes joint optimization, however, when the conditions create an imbalance that optimizes social and technical factors without interaction, unpredictable and unplanned outcomes may occur (Tortorella et al., 2022). Therefore, in the formation of predictive work the identification of social aspects or human factors will require consideration at all three phases of conceptualization, design, and implementation of Industry 4.0 into the existing organization. To carry out this socio-technical framework the design must follow a pattern of "defining the technology, identifying the affected humans, identifying the technology, task scenario analysis and impacts, and outcome analysis" (Neumann, 2021). This implementation process involves data gathering, analysis and interpretation, summarizing the findings, testing the results with stakeholders, and iterating and amending.

2.1.3. Organizational Learning in the Socio-Technical Design Context

Learning is the creation and management of the acquisition of knowledge, skills, and attitudes, which aims to continuously improve employee performance (Gamero, 2018). Organizational learning occurs when new knowledge is integrated into the organization therefore being co-leveraged with current institutional knowledge to enhance systems, routines, rules, and procedures (Haraldseid-Driftland et al., 2023). Organizational agility requires employee adaptability, which is fostered through a socio-technical design of work that encourages

organizational learning and employee empowerment for task discretion. The socio-technical design continues to evolve with the integration of a human-AI operations model, which calls for updated methods of analysis, organizational learning, and autonomy (Fischer et al., 2023). The four major skillsets of AI are perception, understanding, acting, and learning, which expand the logical foundations of input, processing, and output of typical IT systems. AI's attributes contribute to continuous self-optimization, which is ideal for a human-AI collaborative environment (Garrel & Jahn, 2022). Socio-technical workplace design must also consider skills, aptitudes, and control strategies within the human-AI dynamic to include assessments of strategic contributors to collaboration beyond the human-AI duality, collaborations on the shopfloor, impacts of time on collaboration, developed processes for shared control and responsibility, and develop holistic organizational work concepts (Weiss et al., 2023).

A four-step process for transforming work was identified as the 1) developing productionoriented skills, network, and jobs, 2) devise future-centric work designs, 3) create short, medium, and long-term idea models to test, and 4) engage the new idea model and encourage creativity within the practices and culture of the organization (Gratton, 2022).

Organizational learning strengthens preparedness to anticipate and solve problems, as well as navigate change. Long term strategies that involve curating and leveraging data instill an orientation towards learning. Activities contrary to developing a culture of organizational learning and continuous improvement are resistance to change, cultural lock-in, and assumed continuity. Activities in support of a cultural of organizational learning are knowledge sharing, employee engagement, and productivity transparency (Chinoperekweyi et al., 2022).

Principles for jointly optimizing both social and technical aspects of an organization call for continuous learning to be instilled in the strategic vision. Feedback is provided for the

individual and organizational perspectives to contribute to the ongoing development of the social aspects (Fischer et al., 2023). Modern socio-technical system design involves democratic dialogue, which encourages democratic interrelation of stakeholders. Democratic dialogue moves away from the one-directional communication and encompasses two-way dialogue, which is a participatory design process. It is important to note that a close knowledge with the work organization fosters the collaboration and solution focused model of democratic dialogue (Thun et al., 2022). The eight learning principles of using a collaborative approach, creating collaboration across levels of stakeholders and contexts, high flexibility that accommodate time, ensure usability and easy access, highly relevant for context, create space for reflection, create awareness for adaptive capacities, and share examples of good practice were also reported in a recent study (Haraldseid-Driftland et al., 2023).

Productive organizational learning encourages an organization to improve, learn in a productive manner, and engage in organizational inquiry on behalf of the organization. When operational problems arise, employees inquire and recommend new methods of solving them. The development of an organization that values employee learning is a first step to creating autonomy. When productive organizational learning is combined with responsible autonomy and employee control, an environment of socio-technical sustainability is created (Enehaug, 2017).

The socio-technical process of meta-design supports collaborative learning through the design process where system users are designers. The design of the design process itself is considered, due to the technical and social aspects, a greater inclusive socio-technical system. End users are thus designers rather than passive users of the socio-technical system (Cabitza et al., 2020). Five meta-design principles are support for cultures of participation, mechanisms to support empowerment for adaptation and evolution at use time through user-driven adaptability, a

procedure model of seeding, evolutionary growth, and reseeding, semi-structured modeling, and a walkthrough-oriented facilitation (Fischer, 2011).

An enabler to integrating Industry 4.0 within the organization is shared learning, which is found concurrently with activities, such as shared trust, shared visual understanding, and shared user perspectives (Thun et al., 2022). Change agents may also be in place to ensure ongoing education, training, and communication for facilitating a culture of organizational learning (Loh and Koh, 2004).The actions of creating cultures of participation, empowering adaptation, fostering growth, and structuring communication contribute to creating this condition (Fischer & Herrmann, 2011). The competitive advantage of successfully recruiting the best talent may also lie in providing meaningful, challenging, and enjoyable employment.

Also, continuity is observed through organizational learning, which engages employees to improve task completion, job performance, and preventative work. Employees that exert control illustrate greater skill discretion and task authority, which are the foundation of responsible autonomy (Enehaug, 2017). When assessing events or projects the level of employee job control is critical to ensure the diversity of organizational design. Job control leads to employee engagement, which supports continuous learning and coping strategies to respond to disruptions and challenges in workflow processes. Holistically, the professional development of employees who operate under an increased range of mobility leads to increased agility (Gobers, 2023). Socio-technical work design focuses on improving the diversification of task options rather than minimizing them (Fischer et al., 2023). Sgarbossa, F. et al reported that research found a positive correlation between job rotation and job satisfaction (Sgarbossa et al., 2020). Industry 4.0 technologies will alter work strategies, potentially with permanence, therefore understanding the

human factors involved, such as employee experience is critical to averting feelings of reduced autonomy, lessened competence, and counterproductive work behaviors (Grosse, 2023).

2.1.4. Reducing Work Week Schedules in the Socio-Technical Design Context

Industry 4.0 tools are enabling technologies to foster the support of communication and the sharing of information and collaboration between individuals, accessibility, and security to the flow of data, mobility of work times and locations, and improved productivity and working conditions for employees (Cimini & Cavalieri, 2022). As well, flexible work arrangements are a result of trust as a management control strategy (Abgeller et al., 2022).

According to studies of the four-day work week, the results indicated improved employee morale, engagement, and increased productivity (Campbell, 2023). The benefits of flexible work hours are also reduced turnover and absenteeism, increased work-life balance, greater motivation, increased training opportunities and staff qualifications, workplace mobility, and time savings due to lessened travel (Kostadinova & Vladkova, 2022). An increase in job and life satisfaction directly correlates to increased productivity due to the employees' assigned meaning to the tasks. (Ferrara et al., 2022). According to a study conducted by Laursen the autonomy to select work schedules was the most important form of its definition to young workers (Laursen, 2021). AI is increasing in pervasiveness within work systems across industries. Benefits of AI are process improvements and innovation. When developing AI, a socio-technical context must be maintained to ensure that trust is built in through the creation of transparency of the decision-making process and data policies (Werens & von Garrel, 2023).

Employee engagement is essential in strategic planning to achieve desired productivity outcomes when following a four-day work week schedule. When employees view the company as a brand, social interaction is increased among employees, and happiness inspired at work all

positively influence employee performance (Chakraborty et al., 2022). Furthermore, according to a survey respondent of a study conducted by Whiteoak and Sullivan it was stated that family culture is contrary to change, which holds a significantly different meaning other than an employee culture that views the organization as a brand (Whiteoak, 2022).

An earlier study reported by Enehaug showed that the reduced daily work hour goal initiated better coordination and cooperation through the re-scheduling of work shifts. These factors served as a coping mechanism for the employees (Enehaug, 2017). Whiteoak and Sullivan also conducted a socio-technical analysis of a manufacturing firm in Australia to assess the option of instilling a reduced work week goal or other alternative work arrangements. Three main recommendations resulted, which were to integrate a bottom-up approach to job crafting, explore micro-efficiencies, and value quality over quantity in work design as methods to achieve a reduced work week goal (Whiteoak, 2022). Creating time for high-quality focus, collaboration, and reducing distractions and inefficiencies is essential (Pang, 2020). Prioritizing working hours and ensuring the brain functions at its best support collective efficiency (Abildgaard, 2019).

Socio-technical theory encourages that as the workflow process is more simplified to incentivize employee involvement that the tasks are enriched to create a more varied and humane working environment. The goal is that this strategic action espouses innovation in the organization and results in increased productivity. The ability to oversee unexpected events and deal with problem solving for the employee is also addressed in this activity (Klemsdal et al., 2017). As an example, a study of modern socio-technical theory when applied develops opportunities to reduce the frequency of repetitive jobs in an organization, such as through integrating interventions such as the creation of semi-autonomous teams (Vermeerbergen et al.,

2021). This study outcome is in line with the socio-technical concept of responsible autonomy and autonomous work groups (Guest et al., 2022).

2.1.5. Practicing Responsible Autonomy in the Socio-Technical Design Context

An employee's responsible autonomy is a core value of the socio-technical design process (Flinchbaugh et al., 2016). As outlined by Yadav et al. the socio-technical criterion described by Cherns discussed as eliminating or controlling variances as close to the point of origin as possible refers to allowing employees to learn from mistakes, if applicable, and involves the freedom to conduct 'self-inspection' (Yadav et al., 2017). The socio-technical system theory notes that responsible autonomy describes the collective learning of employees to ensure skillsets are developed to promote a more independently self-governed work organization. Sustainability is supported by employees' autonomy and control of workplace conditions, in other words selfleadership (Amble, 2013). Furthermore, autonomy represents the employee's freedom, independence, and discretion to determine methods of completing work and choice in selecting work schedules (van Kleeff et al., 2023). Work design considers both the physical and mental aspects to ensure the feasibility, safety, and relevancy of tasks to promote job satisfaction and personal development (Stern & Becker, 2019). Studies have found that employee training, empowerment and job-enrichment partnered with 'worker task capability' and 'flexibility in staffing' are connected to the successful implementation of Industry 4.0 (Das and Jayaram, 2007).

The goal of Industry 4.0 is to gain autonomy, decentralization, responsibility, and teamwork (Tortorella et al., 2022). To achieve responsible autonomy leadership takes a significant role in creating a work environment that supports flexibility in an employee's place and time of work. When employees find meaning in their work and have the ability to customize technology, increased productivity is observed (Fischer et al., 2023). Designing a socio-technical organization

jointly optimizes both technical and social systems, which aligns with the employee's values thereby creating greater trust and job satisfaction (Liscio et al., 2023). Primary job characteristics that are desired are described as encompassing skill variety, task meaning, task identity, autonomy, and feedback (Kwiotkowska & Gebczynska, 2022). Research illustrates that improving an employee's autonomy and task discretion correlates directly to perceived benefit of flexible work arrangements (Tortorella et. al, 2023).

The meaning of work may be derived from an employee's motivation to determine their tasks physically and cognitively. Several job crafting practices exist, such as amending task boundaries and the quantity of tasks completed. In terms of cognitive crafting, the task boundaries and perception of work are open to change by the employee. An additional aspect of job crafting is defining the social interactions and frequency thereof in the workplace setting. Reasons for job crafting include employee control, meaning, socialization, and employee self-identity, which are all significant factors during a period of digital transformation. Learning algorithms may divert employees to strengthening their focus on the development of the social aspects within the sociotechnical work organization. Social aspects include the people, culture, and goals and may be focused on redefining the meaning of work. (Perez et al., 2022).

One method of completing work, such as creating cross-functional diagrams of processes and resources, helps to identify the root cause of factors impacting workflow times and identifying the relationships influencing outcomes that occur (Alsakka et al., 2023). Crossfunctional diagrams encourage the design of adaptation, dynamic cooperation, and work distribution (Pacaux-Lemoine et al., 2022). To support employee autonomy cross-functional diagrams aid in providing discretion to design workflows to jointly optimize both technical and human factors, which assists with managing work demands and therefore reduces the potential for employee burnout. The mapping of interrelated activities and resources jointly by management and employees assists with accurately setting productivity goals, employee appraisals, and reduced work hours (Delaney & Casey, 2023). A digital leadership will encourage the creative use of technology to espouse employee motivation, productivity, and efficient resource allocation, thus strengthening organizational capacity (Shin et al., 2023).

2.1.6. Leading in the Socio-Technical Design Context

As businesses respond to increased product and service customization requirements, the upskilling of employees to manage digital technologies will be valuable (Achieng, 2022). The World Economic Forum's report on the future of work highlights these ten job skills: creativity, emotional intelligence, analytical thinking, active learning, judgment and decision making, interpersonal communication skills, leadership skills, diversity and cultural intelligence, technology skills, and embracing change (Szabo, P. et al., 2023). Developing cross-functional teams allows for a bottom-up leadership approach where employees lead communication efforts to effectively integrate digital transformation. This communication structure is agile as it allows for the diffusion of operational information and innovation for the purpose of creating value and supporting an organization's most successful strategic objectives within the internal and external subsystems of a socio-technical system (Leso et al., 2022)(Whiteoak, 2022). The bottom-up leadership style, also considered a self-organizing manufacturing system, is a decentralized approach to problem-solving as it involves diverse communication sources (Maltseva et al., 2022). The employees are integral to the production process and can therefore leverage in-depth their industrial knowledge to impart qualitative and quantitative data to contribute to continuous improvement and knowledge creation (Colombari & Neirotti, 2023). In digital transformation employees' roles may change to incorporate tasks that are more engineering in nature, such as

process control or continuous improvement, which will require a mindset of ongoing training (Waschull et al., 2022). As well, another critical soft skill in Industry 4.0 is an agile mindset (Lima et al., 2023). This mindset allows the organization to weather external market forces that are supported by Industry 4.0 (Kohnova & Salajova, 2023).

Communicating as an organizational unit across departments and teams allows employees to identify areas of improvement that lead to greater operational efficiencies. This strategy provides an antecedent to moving to a reduced work week schedule (Whiteoak, 2022). A flexible organization activates the involvement of a variety of teams, units, and organizations for which the system design will be utilized (Haraldseid-Driftland et al., 2023). A digital leadership that understands that as the employee base becomes more decentralized, methods of long distant employee motivation and coordination will be crucial to performance success (Hirsch-Kreinsen, 2023). Mutually transferring knowledge across all organizational levels will elevate the employee to the role of knowledge worker (Davies et al., 2017). Allowing for the continuous facilitation of employee training and feedback strengthens employee engagement and therefore operational effectiveness (van Kleeff et al., 2023).

Leadership characteristics such as promoting self-awareness, listening, serving those on the team, helping people grow, coaching versus controlling, promoting safety, respect, and trust, and promoting the energy and intelligence of others are critical skills. (Project Management Institute, 2017). To maintain a high-level of employee trust, the development of standard operating procedures to guide the implementation of Industry 4.0 is essential. Standard operation procedures represent the technical subsystem of a socio-technical system. They provide a useful guide for an organization to prioritize processes carrying out digital transformation. The work processes, systems architecture and data formats are then assessed to strategize the purpose for

digital integration, data use, employee use, and return on investment (Budde et al., 2022). When an organization holistically agrees upon these organizational procedures, a greater propensity for the robust adoption of Industry 4.0 is ensured (Liu et al., 2022).

Employee learning is a continuous process to maintain, as it fosters a sustainable growth advantage of trained personnel. Opportunities for employees to learn and encourage each other to learn, as well as provide feedback will support new technology adoption (Chaudhuri et al., 2023). A flat organization rather than a hierarchical leadership structure provides a suitable environment for digital transformation as this represents an employee base with greater engagement and responsible autonomy. These organizational characteristics espouse a flexible, agile, learning, innovative, and communicative culture. Organizations that have exhibited a contrary structure have experienced lower levels of technology adoption. According to the socio-technical systems framework provided by Davis et al., the six internal subsystems of people, culture, goals, processes, infrastructure, and technology are all equally important to strategically build internal capacity within to ensure successful interoperability and dynamic performance (Sergei et al., 2023). Dynamic performance anticipates external opportunities and threats, assumes opportunities, and achieves competitive advantages through continuous improvement and the reconfiguration of intangible and tangible organizational resources (Bag et al., 2021).

Organizational flexibility may be observed in the contexts of part or product and process, which may be completed utilizing a variety of equipment, processes, and resources. Flexibility is achieved through the aggregate planning among various operational functions (Salunkhe & Berglund, 2022).

2.1.7. Understanding the Impact of Industry 4.0 in the United States and Worldwide

According to a study conducted by Michulek and Gajanova, publications on the topic of Industry 4.0 were assessed during the 2016-2022 timeframe. The number of total publications on the topic of Industry 4.0 during the 2016 -2022 on the Web of Science database is trending as follows:

- 1. Germany 2450
- 2. Italy $-2,318$
- 3. China 1,515
- 4. USA 1,220
- 5. India 1,198
- 6. Great Britain $-1,277$
	- a. England $-1,064$
	- b. Scotland -121
	- c. Wales -69
	- d. Northern Ireland 23 (Michulek & Gajanova, 2023).

A separate study utilized the Web of Science Core Collection to assess the academic literature published in 2018 on the topics of artificial intelligence, big data and the internet of things to identify the top 20 countries researching these fields. In the order of the number of significant contributions from most to least frequent on the topic of artificial intelligence, they found that China, USA, Korea, India, England, Italy, Spain, Australia, Germany, Japan, Taiwan, Canada, Iran, France, Brazil, Saudi Arabia, Malaysia, Turkey, Netherlands, and Pakistan were the academic research presence in the field. With regards to the United Kingdom of Great Britain and Northern Ireland, they found that England had the most publications, followed by Scotland, then Wales, and finally Northern Ireland (Mizukami and Nakano, 2022).

Furthermore, another study conducted a cluster analysis of the 33 European Union countries and classified groups of countries according to similarities in Industry 4.0 performance. Cluster 1 represented France, Portugal, Malta, Slovenia, Luxembourg, Austria, Spain, Cyprus and Italy. Cluster 2 represented Belgium, Germany, Netherlands, Sweden, Norway, Denmark, Finland, and Lithuania. Cluster 3 represents Bulgaria, Greece, and Romania. Cluster 4 represents Hungary, Turkey, Latvia, Poland, Macedonia, and Serbia. Finally, Cluster 5 represents Croatia, Slovakia, Czech Republic, Estonia, UK, Ireland, and Iceland (Atik and Unlu, 2019).

Moreover, fifteen countries throughout the world have initiated industrial plans to move Industry 4.0 forward within their respective geographic and economic contexts. The countries and their initiatives are as follows:

- Australia Industry 4.0 Testlabs
- Belgium Made Different
- Denmark Manufacturing Academy of Denmark (MADE)
- France Industrie du Futur
- Germany Germany: Industrie 4.0
- Italy Impresa 4.0
- Japan Society 5.0
- The Netherlands Smart Industry
- People's Republic of China Made in China 2025
- Portugal Industria 4.0
- Singapore Research, Innovation and Enterprise 2020 Plan
- South Korea Manufacturing Industry Innovation 3.0
- Spain Industria Conectada 4.0
- The United Kingdom The Future of Manufacturing
- The United State of America Advanced Manufacturing Partnership (Yang, F. and Gu, S., 2021).

More recently the Office of the European Union has published a report in 2023 titled "Analytical insights into the global digital ecosystem" (Calza et al., 2023). The shared insights provided by the EU's Joint Research Center highlighted the following items.

- 1. The digital profile of China, the largest competitor of the U.S., indicates that dynamic data, artificial intelligence, autonomous systems, robotics have a significant presence. As well, in the U.S. the infrastructure, cloud computing, artificial intelligence, and dynamic data are key. In the E.U., infrastructure, cloud computing, dynamic data, and artificial intelligence are leading investments. In the rest of the world, infrastructure, cloud computing, dynamic data, semiconductors, and power electronics are key investments.
- 2. It is interesting to point out that in the U.S.'s digital profile that dynamic data is focused on less than that in the China, E.U., and the rest of the world. Also, the U.S. does not include in its digital profile a significant investment in the Internet of Things.
- 3. In contrast, China's digital profile includes infrastructure, cloud computing, and the internet of things as far lesser investments at 5%, respectively.
- 4. The E.U. displays the highest strategic value, which suggests a strategic position in the network of Research & Innovation activities, such as patent applications, in autonomous systems. This may be due to the fact that the E.U. players display an intense collaboration with players located outside the E.U., implying that the E.U. may be in the position to act

as bridge or as bottleneck controlling the flow of knowledge through this specific network representation of the global digital ecosystem.

- 5. China dominates the autonomous system category in terms of the level of engagement. The strategic position of China is lower, which may indicate fewer Research & Innovation activities, such as patent applications.
- 6. The engagement level in the U.S. is slightly greater than in the E.U. However, the strategic position is at least half of the E.U. This may indicate fewer patent applications. The rest of the world illustrated aggregately far less strategic positions and engagement activity than the E.U., China, and the U.S.
- 7. The U.S. leads in the Industry 4.0 fields of infrastructure/cloud computing and cyber security. U.S. businesses place a close second in the integration of artificial intelligence to China.
- 8. In the U.S. the organizations leveraging Industry 4.0 are primarily businesses, followed by research institutions and universities. There is a nominal representation by government organizations.
- 9. In contrast China has more businesses leveraging Industry 4.0 than the U.S., European Union and the rest of the world.
- 10. As well, there is significantly more representation of Industry 4.0 usage among China's research institutions, universities, and government agencies. (Calza et al., 2023).

2.1.8. Integrating Industry 5.0 into the Industry 4.0 Context

Industry 4.0's purpose coordinates distributed information and communication technologies with operational technology within a cyber-physical system allowing a human operator to ensure the ability to mass customize and personalize through intelligence (Michulek & Gajanova, 2023). Industry 4.0's emphasis is lacking a focus on the promotion of social aspects and the consideration for environmental conservation (Ghobakhloo et al., 2022).

Industry 5.0 is the continued development of Industry 4.0 to one that is sustainable and resilient and that emphasizes digital sustainability, environmental awareness, and humancenteredness. As an example, smart quality management focuses on research and innovation as a human-centered role. (Bajic et al., 2023). Sustainability has been defined as meeting the present organizational needs without jeopardizing the future requirements. Sustainability in the Industry 4.0 context are the economic, ecological, social, and corporate social responsibility factors. This aim is achieved through the 6R approach of reducing resource dependency, reusing end-of-life products and components, recycle waste materials into materials, redesigning recovered materials and resources for new product lines, recovering products at the end of the stage, and remanufacturing or restoring products for future use (Dossou et al., 2022).

Industry 5.0 has also been described as that it "reflects the value of humanistic care and integrates human subjectivity and intellect with the effectiveness, artificial intelligence, and accuracy of robots in industrial production, accomplishing the progression toward the symbiotic ecosystem" (Michulek and Gajanova, 2023). The Triple Bottom Line is the term used to describe the aim of measuring performance in Industry 5.0 around environmental, social, and economic goals (Dossou et al., 2022).

The circular economy represents this pull towards sustainability, as it is described as a practice of retrofitting industries to improve reusing, remanufacturing, and the reduction of waste resources. Fundamental to this initiative is to "preserve and enhance natural capital", "optimize resource yields" and "foster systems effectiveness" (Varbanova et al., 2023). The circular

economy has been referred to as "a business model focusing on the entire economy" as it focuses on perpetuating the solutions (Dossou et al., 2022).

Industry 5.0 focuses on integrating cognitive computing and the Internet of Things and, according to a report on Europe's industrial future, it should be viewed as a continuous evolution of Industry 4.0. Industry 5.0's imperative is to move away from the techno-centricity and the digital divide that has marred Industry 4.0 and transition to energy transition technologies, smart materials, and cognitive artificial intelligence. Industry 5.0's focus on elevating the importance of social factors in the use of Industry 4.0 technologies eases the digital divide and facilitates equitable development.

Five key characteristics define Industry 5.0. They are as follows: sustainable development and performance-driven competitiveness, human resource centered strategies inform the digital transformation, value chain expansion using standards and effective technologies, an emphasis on stakeholder engagement throughout innovation cycle, technology management, and sustainability management, and innovation with a core alignment with environmental sustainability (Espina-Romero et al., 2023).

Sustainable industrial development has been described as building digital transformation competency, eco-innovation (environmental and social), stakeholder collaboration and integration, sustainability orientation and performance management, sustainable value network composition, and corporate and technology governance (Ghobakhloo et al., 2022). The sociotechnical systems theory is also a potential enabler for Industry 5.0 researchers to explore, as this agenda aligns with the theory's core impetus of jointly optimizing both social and technical factors of the work organization.

Data researchers implement smart manufacturing systems in Industry 5.0. To carry out the integration they must understand the workflow processes to select the appropriate data to analyze and model, such as through the real-time big data collection and processing methods of edge computing in order to prepare small data sets to identify significant information (Bajic et al., 2023). The following countries have published the most academic research on measuring the sustainable performance of SMEs that are undergoing digital transformation – Italy, China, Finland, Indonesia, and the UK (Melo et al., 2023). The following countries are ranked as to the level of contribution of published content on the topic of Industry 5.0.

- 1. China
- 2. India
- 3. USA
- 4. Italy
- 5. Great Britain (Michulek & Gajanova, 2023).

The number of total publications on the topic of Industry 5.0 during the 2016 -2022 on the Web of

Science database is trending as follows:

- 1. $2016 1$
- 2. $2017 0$
- 3. $2018 2$
- 4. $2019 10$
- 5. $2020 21$
- 6. $2021 58$
- 7. 2022 201 (Michulek & Gajanova, 2023).

The key enabling technologies of Industry 5.0 that have inclusive, sustainable, valuesensitive, and universal design attributes have been noted as cognitive artificial intelligence, extended reality, human interaction and recognition technologies, cognitive cyber-physical systems, industrial smart wearable, intelligent energy management systems, intelligent or adaptive robots, dynamic simulation and digital twin, and smart product lifecycle management (Agote-Garrido et al., 2023).

2.1.9. Implementing Industry 4.0 by Utilizing a Socio-Technical SWOT Analysis

When focusing on the implementation of Industry 4.0 in the small and medium-sized enterprise context, it is imperative to consider the "how", "what", and "why" scenarios of the future development of the smart manufacturer. (Grefen et al., 2022). The Industry 4.0 integration will have impacts throughout the entire organization, such as with the production, administration and control, human resources, and inventory and warehouse management departments. Understanding the strategic and tangible benefits with regards to resource utilization, expenditures, risks, and scheduling is essential (Loh and Koh, 2004).

A SWOT analysis is the review of the strengths, weaknesses, opportunities, and threats of an organization to understand the formal position of the organizational structure both internally and throughout the supply chain network external to the manufacturer. Examples of items to be assessed include internal and external support, knowledgeable staff, technological infrastructure available, collaborative partnerships, skill development, and employee engagement (Mian et al., 2020). Also, successful Industry 4.0 implementation will be reliant on internal management skills, value chain readiness, and internal technological maturity (Roy et al., 2023).

A business model canvas, which was created by Osterwalder and Pigneur, is a helpful strategic planning tool and will be created after the completion of the socio-technical SWOT

analysis by the organization. The business model canvas serves as a guide to understanding how the organization creates, delivers, and attains value (Nuryani et al., 2023). This business development tool considers the nine core elements of an organization such as the key partners, key activities, key resources, value proposition, customer relationships, channels, customer segments, cost structure, and revenue streams (SK, 2020).

The first socio-technical survey focuses on the five socio-technical system's theoretical framework aspects. These are data gathering, analysis and interpretation, summarization, testing, iterating and amending as displayed in Table 4 (Roth and Farahmand, 2023). The second sociotechnical survey focuses on the six subsystems outlined by Davis et al. These are goals, people, processes, building/infrastructure, technology, and culture that are embedded within an external environment comprised of stakeholders, financial considerations, and regulatory frameworks. The socio-technical system framework highlights areas requiring design process improvements, underlines an interrelated perspective approach, serves as a guide for systems analysis, and supports enabling forecasts on future systems operation (Davis et al., 2014). A socio-technical SWOT analysis will be developed for each of the eleven socio-technical constructs to inform the development of the business model canvas as illustrated in Table 1.

Implementation tools supporting the development of real-time data schema involved and the interoperability levels observed assist with resource management and optimization (Namugenyi et al., 2019). Socio-technical system (STS) surveys will be issued using a five-level Likert scale from *Extremely Unlikely* to *Extremely Likely* to calculate Pearson and Polychoric Correlation Coefficients. Feedback from employees, customers, suppliers, bankers, friends in other organizations, consultants, government reports, and association meetings is reviewed in the socio-technical SWOT analysis in the first business phase and in subsequent technology,

resilience and innovation phases to ensure the instilling of socio-technical joint optimization of both technical and social factors throughout the Industry 4.0 implementation process and to conduct additional statistical analyses (Daft, R., 2021). Feedback from employees populate the internal strengths and weaknesses columns; feedback from both internal and external parties populates the opportunities and threats columns. These survey results inform the development of a digital socio-technical scorecard in an enterprise resource planning software to visually represent the organization's current socio-technical status and to automate this project management assessment tool (Bradford, M., 2015) (Schwalbe, K., 2006).

Socio- technical Construct: Processes	Socio- Technical Survey Question	Strengths	Weaknesses	Opportunities	Threats
	Q20	5 (Please $describe - i.e.$ standard operating procedure creating)		$\overline{4}$ (Please $describe - i.e.$ updated standard operating procedure provides new guidance to employees encouraging responsible autonomy)	
	Q ₆		$\overline{4}$ (Please describe - cross- functional diagrams created infrequently)		5 (Please describe- competitors may be reaching more suppliers with clearly presented data)
	$Q5$ etc.	5 (Please $describe - i.e.$ infographics provided to employees on key performance indicators)		$\overline{4}$ (Please $describe - i.e.$ opportunity to create learning module from information to support continuous learning)	
	Total	10	$\overline{4}$	8	\mathfrak{S}

Table 1. Proposed Socio-technical SWOT Analysis Framework Based on Davis et al.

The emphasis on the individual's tasks is core to the socio-technical perspective (Haring et al., 2023). As well, assessing the data collected during this timeframe is imperative to verify if it reveals new information to facilitate a response (Pech and Vrchota, 2020). An expertise in project management, change management, an adaptive culture, a clear business plan and vision, management support, skilled staff, testing, process simplification, appropriate software development, effective communication, continuous monitoring, and a performance evaluation of the system are also critical factors to implementing newer technologies. Requesting, collecting, and measuring user input is also essential to verifying the alignment to the organization's strategic and tangible requirements (Loh and Koh, 2004).

A study provided by Liu et al. illustrated a reference framework for SMEs to implement digital transformation with IoT and cloud computing. The implementation flow begins with addressing the business model to define product features then moves to the technical requirements and addresses the innovation. (Liu et al., 2021). Manufacturing networks that utilize collaborative business models have more flexible Industry 4.0 implementation opportunities (Grefen et al., 2022). Figure 1 is based on the Industry 4.0 implementation model for SMEs by Liu et al, however, it has been modified by the author to include the elements of the Socio-Technical SWOT analysis, which incorporates the two socio-technical survey tools, and the organizational resilience phase to dually consider Industry 4.0 and Industry 5.0 strategies.

Figure 1. Proposed Framework for Socio-technical Design of Industry 4.0 Implementation with Industry 5.0 Resiliency and Socio-Technical SWOT Analysis

The phases provide technical requirements that may be defined as functional (e.g. monitoring motion) and characteristics (e.g. assessing real-time data). In the technology phase the connectivity, computing, and intelligence of the Industry 4.0 solution are considered within a step. The third phase of resilience focuses on building organizational resilience. The resiliency initiative begins with the employee identifying non-routine operational occurrences and using their training and leadership skills to resolve issues. Organizational risk plans and prevention techniques address resilience capacity building. The technological focus for building resiliency will involve a decentralized peer-to-peer network with the full integration of secured information transfer capability across departments, levels, and processes using smart platforms (Zizic et al., 2022). Therefore, resilience is about operational recovery issues, as well as adaptation and operational efficiency topics (Agote-Garrido et al., 2023).

The innovation phase first starts with the steps of research, design, and prototyping. Research entails understanding the end-user requirements; designing expresses the problem and identifies problem solutions; and prototyping is the process of creating the minimum viable

solution for the end-user. The innovation principles of integration and partition are employed, where partition intends to separate the functions or services from products and foster the growth of the one that has the most potential to develop into a viable new commercial opportunity. Partition in technology refers to dividing software into various modules to increase the beneficial outcomes. The integration principle of innovation implies that there is a new configuration of functions or services to create a new process or product thereby. (Liu et al., 2021). The testing phase occurs after prototyping and is the process of learning and iterating to find the right combination of elements for a market-ready solution that is technologically and economically feasible. This is followed by the socio-technical SWOT analysis to determine the joint optimization of social and technical elements in the innovation stage.

Innovations may be in the form of a technological or business application or both. Innovations are often customer-oriented and are therefore most often externally motivated (Grefen et al., 2022). Representing a series of function blocks that verify the Industry 4.0 implementation process are the functional requirements, intermediate functional requirements aligning with the automation requirement, the characteristic requirements, and lastly the function blocks expressing the hardware requirements (Liu et al., 2021). Resources expended to create these function blocks should closely align to the core value proposition of the organization's business model and must be iterated to ensure continuous competitive advantage in the market. Defining, measuring, analyzing, improving, and controlling and designing is therefore an ongoing process (Dossou et al., 2022). A bottom-up design approach will identify the specific software components to correspond with the macro-level IT architecture requirements (Grefen et al., 2022). Lastly, ensuring employees embrace a mindset of environmental consciousness during the digital transformation may promote organization-wide carbon reduction initiatives, as well as lead to the

promotion of green innovation (Gao, 2023). A socio-technical survey is conducted and the user feedback assessed for contributions to the implementation process.

2.1.10. Evaluating Digital Transformation – A Socio-Technical Assessment Model

"Technology is the most powerful shaping force on the planet and its individual impact is most evident in human factors" (Peireira et al., 2023). The academic research is supported with the proposal of modeling the interdependencies of the factors of a socio-technical system to improve adaptability, sustainability, efficiency, employee well-being, and effectiveness. The purpose of the modeling of a socio-technical system is to design, create, and reengineer holistically and systemically at all levels of the work organization. These tools aid employee decision-making in creating successful and sustainable value within an organization in a volatile, uncertain, complex, and ambiguous external environment (Lima et al., 2023). Intentionally using the survey tools to assess the level of human-centricity in the use of cyber objects – such as the decision-making system of digital twins, control systems – such as multi-agent shop floor systems, and physical objects – such as the communication role among logistics systems will ensure that human factors are thoroughly instilled throughout the socio-technical system architecture in the Industry 4.0 context (Bhattacharya et al., 2023). As well, the surveys' use among diverse skillsets and task types will encourage a collection of primary workforce data from both men and women to assess the gender neutrality of intelligent systems in a complex sociotechnical environment (Maggioli & Cunha, 2023). The mathematical models noted in this chapter may be applied across industries.

This study of socio-technical readiness and organizational attributes leading to reduced work week schedules under the conditions of Industry 4.0 should be carried out by means of periodic collection of statistical information from data retained in the first and second surveys on

the socio-technical constructs of data gathering, analysis and interpretation, summarization, testing, iterating and amending, responsible autonomy, productivity and innovation, organizational learning, technology implementation, resource allocation, and bottom-up communication indicators, and with the guide of the suggested mathematical models. The sociotechnical constructs account for diverse learning styles, which is significant when considering the intergenerational age of the manufacturing industry. Tables 2 and 3 below provide the legends of the socio-technical indicators for the two survey tools.

Table 3. Legend for the Second Socio-technical Survey Tool

The first and second survey tools will also serve to provide an avenue for the employees to feel empowered to share their knowledge and contribute to the design of their job and the essential training. Additionally, they provide an open forum that leads to directly highlighting and developing worker competencies (Ávila-Gutiérrez et al., 2021).

It is recommended that the surveys are preliminarily conducted among all employees as part of a socio-technical SWOT analysis prior to developing the business model for Industry 4.0 integration. This socio-technical assessment tool is implemented in the technology, resilience, and innovation phases. Thereafter, a continued maintenance testing timeframe for the model could emulate that of the four-day work week initiatives, such as through the Four Day Work Week Global Foundation, where a two-month orientation program followed by a six-month commitment to

programmatic initiatives is instituted (Schor et al., 2022). After the two-month orientation program, the survey tools will be sent to employees a second time. After the six-month trial period, the survey tools will be sent out to employees a third time (Shpak et al., 2019). Thereafter, the collection of data through the consolidated survey tools will be conducted quarterly. Depending on the length of the Industry 4.0 implementation phase, there may be more than one survey period.

Pearson and Polychoric coefficient values will be produced from the first and second survey responses and will provide insights into the successful level of integration of the sociotechnical construct, as well as the successful transition or correlation among socio-technical constructs. These coefficient values will be inputted in the mathematical models in the figures below. According to the results of the mathematical model calculation, the evaluation and prediction of the state of development of joint optimization socio-technical factors in the work organization, the socio-technical readiness to adopt Industry 4.0, and the preparedness to instill four-day work week initiatives will be determined. As well, the surveys will provide data on the stability and efficiency of the development of socio-technical factors within the firm.

Figure 2 depicts the Pearson and Polychoric coefficient formula for the first survey tool. As the coefficients are often expressed as two or three numerical values behind the decimal point, this may also be conversely translated into a percentage value. The closer the number is to one (1), the higher the level of socio-technical construct integration and therefore the more robust the stability of the socio-technical readiness is present in the design framework. When this coefficient value is inputted into the relationship model, as is seen in the example provided in Figure 3, as the outcome approaches zero (0), the more likely the work organization is operating with jointly optimized social and technical factors and is thus a socio-technically designed framework.

$$
S = 5 - (rc_1 + rc_2 + rc_3 + rc_4 + rc_5)
$$

Figure 2. Example of the Socio-technical Relationship Model used with the First Survey Data

Figure 3. Example of Socio-technical Relationship Model Used to Test the Level of Sociotechnical Joint Optimization within an Organization

In reference to the Polychoric and Pearson correlation coefficient outcomes represented in the tables in the next chapter from small, medium, and large-sized manufacturers and their corresponding relationships among the socio-technical indicators, assumptions are made that values within a 98% threshold or higher for socio-technical constructs C1 through C5 may indicate that one is more likely to observe a positive relationship between Industry 4.0 integration (Q12) and Increased Productivity (Q21) based on the increased level of socio-technical organizational design implemented. Thus, the greater the socio-technical readiness the greater the organization's aptitude for integrating Industry 4.0. Again, the example illustrated in Figure 4 provides a visual of the assumption that an 'S' value or Socio-technical Readiness value of zero (0) to .10 equates to a near perfect score of 98% to 100% socio-technical design implementation. Figure 4 displays the assumed acceptable range of the 'S' value to observe increased productivity per employee based on socio-technical design.

 $P(\text{IP}) = .10$ (Collective Socio-technical Readiness Maximum Value) to 0 (Collective Sociotechnical Readiness Optimal Value)

Figure 4. The Relationship Model of the Acceptable Range of 'S' Value to Observe Increased Productivity Per Employee Based on Socio-technical Design

Socio-technical Readiness = Industry 4.0 Integration Aptitude

Figure 5. The Relationship Model of the Socio-technical Readiness and Industry 4.0 Adoption

The theoretical principles of socio-technical design in the Industry 5.0 context encourage the full integration of technological, social, and environmental priorities in the modern digital transformation. The inclusivity of human-centric approaches develops and encourages effective human-machine co-working. This is core to the concept of Industry 5.0, which leads to creating a more sustainable and resilient work organization and realizes the deficits incumbent of a purely techno-centric approach to organizational design (Peruzzini et al., 2023).

Figure 6 describes the recommended approach to deciphering, designing, constructing, and reorganizing socio-technical factors within complex social and technical systems under the conditions of both pre and post Industry 4.0 adoption contexts. The Reduced Daily Work Hour Goal equates to the numerical value of six (6) possible outcomes at a value of one (1) or 100% for each subtracted from the summation of Polychoric and/or Pearson correlation coefficients of the second survey results for responsible autonomy, productivity & innovation, organizational learning, resource allocation, technology implementation, bottom-up communication, and sociotechnical readiness value from the first survey tool.

$$
RD = 6 - (r_{RA} + r_{PI} + r_{OL} + r_{RE} + r_T + r_C) - S
$$

Figure 6. The Relationship Model for Achieving a Reduced Daily Work Hour Goal Using the First and Second Survey Results

The desired reduced daily work hour goal range is between .12 and -0.1, where the closer the value is to zero (0), the greater the effectiveness of the socio-technical design framework. The opportunity for a reduced daily work hour goal is greater. We assume from the first survey relationships that a Polychoric and/or Pearson Correlation Coefficient value of .98 or higher for

each construct is needed to observe greater operational efficiencies in the socio-economic landscape of Minnesota and North Dakota to result in increased productivity performance. This is expressed in an example illustrated in Figure 7. Each of the variables have been described by academic researchers as integral to the success of the six socio-technical constructs of people, culture, goals, technology, process/procedures, and infrastructure. The six variables employed in the mathematical model also integrate Industry 5.0 concepts, such as innovation, use of data (resource allocation), collaboration between machines and humans and the role of humans in the cyber-physical production setting (Bhattacharya et al., 2023). We assume that the characteristics observed provide a greater opportunity for realizing a reduced daily work hour goal. Figure 7 also highlights the blending of Industry 4.0 technology implementation with Industry 5.0 principles of the integration of human cognition, ethics, and social responsibility (Peireira, A. et al, 2023).

Where $S = .10$ to 0 [from first survey result]

Example: $RD = 6 - (.98 + .98 + .98 + .98 + .98 + .98 + .98 + .98) - .10$

 $RD = .02$

Figure 7. Example of the Reduced Daily Work Hour Goal Relationship Model in Use

Understanding how humans interact with smart devices is becoming increasingly necessary. The use of the two survey tools in combination with the relationship models allow for the deliberate and helpful curation of training data to inform future decision-making with regards to human operator work design in Industry 4.0 and Industry 5.0 contexts. One possible opportunity of the model's utility is its deployment when assessing the human-centric success of job rotation scheduling outcomes. These methodological steps diligently gather useful metrics that add value. The focus is on creating a more unified evaluation framework to assess performance

indicators that make transparent the benefits and challenges to integrating human factors into AI environments (Bhattacharya et al., 2023). The transition to Industry 5.0 will require that humans provide creativity to the workflow process when using artificial intelligence systems. Beyond the necessity of digital work skills in AI, data analysis, cyber security, and knowledge management, the independent thinking, flexible, and entrepreneurial worker will be essential in driving this new work paradigm (Lin & Wang, 2022). The modeling also contributes to Industry 5.0's call of action to "recognize, reconsider, realize, reduce, reuse, and recycle", which is a method of optimizing material utilization and logistics, therefore increasing sustainability efforts. The appraisal of work-life balance, innovation processes, and high-level product and service customization will be its outputs (Mourtzis et al., 2022).

The limitation of this study is that the mathematical model was designed from a small sample of manufacturers within a specific socio-economic context of Minnesota and North Dakota. The representation of the breadth of the industrial sector may not be fully illustrated. Another limitation is the lack of validation of the models in the use of an applied workforce context, such as a longitudinal study. The performance indicators that have been significantly recommended by academic researchers may need to bare the weight of added review.

Future studies will test the proposed relationship models for estimating and predicting the state of development of socio-technical factors. The movement to implement Industry 4.0 and move to Industry 5.0 with the closer connectivity of human factors to the newer communication and information technologies is upon us as challenges, such as large-scale job automation through technology, must be directly addressed (Maggioli & Cunha, 2023). According to a 2022 survey conducted by Employbridge, over 19,000 manufacturing and warehouse employees in the United States consider flexibility in work schedules as integral to job retention. Another recent study
supported this assertion that flexible job rotation plans build knowledge, skills, and abilities among employees by energizing them with a variety of tasks within short timeframes (Battini et al., 2022). The Operator 5.0 will be a knowledge worker using innovative technologies to create increased operational efficiencies within the manufacturing system. Engaged employees are happy and fully integrated into the socio-technical design, which leads to increased productivity, innovation, competitive advantage, and reduced recidivism (Salvadorinho & Teixeira, 2023).

3. RESEARCH METHODOLOGY

This chapter focuses on the purpose of the study, research questions and hypotheses, research design, target population and sample, procedures, instrumentation, and ethical considerations. The methods to conduct research that develops a socio-technical systems design instrument to support the implementation of Industry 4.0 are supported in this research. The design elements of research, such as the unit of analysis, respondent industry, sample size, and survey administration are described. As well, the measurement items and the method used for analysis are included in this section.

3.1. Purpose of Study

The purpose of the qualitative survey-based research study is to further advance the sociotechnical systems theory as method of increasing the adoption of new communication and information technologies of Industry 4.0 among manufacturers in Minnesota and North Dakota. The socio-technical systems theory was assessed through comparing the parameters of 11 sociotechnical constructs comprised of forty-five (45) questions that were provided on two survey instruments to receive multilevel employee perceptions among Minnesota and North Dakota manufacturers of socio-technical system design and digital maturity factors. These survey questionnaires are included in the following Ch. 4 Results section. The research insights provided through the completion of these survey instruments may guide or increase the Industry 4.0 implementation through prognostic and diagnostic analyses.

Figure 8. Socio-technical Constructs Researched

3.2. Research Questions and Hypotheses

This qualitative research questionnaire was founded on the unit of analysis of the employee's perspective of socio-technical systems design within the organization and the organization's digital maturity level. The two survey instruments posed forty-five questions collectively that reviewed the parameters of 11 socio-technical constructs within socio-technical systems design, demographic information, assessed digital maturity and Industry 4.0 integration levels. Figure 9 illustrates the socio-technical research framework. The following are the hypotheses and research questions.

- 1) Hypothesis 1: The socio-technical design principles will be applicable in the Industry 4.0 context among North Dakota and Minnesota manufacturers.
- Research Question 1: How applicable are socio-technical design principles in the Industry 4.0 context among North Dakota and Minnesota manufacturers?
	- 2) Hypothesis 2: There is a positive correlation between Industry 4.0 and increased productivity among manufacturers in Minnesota and North Dakota.

Research Question 2: Is there a positive correlation between Industry 4.0 and increased productivity among manufacturers in Minnesota and North Dakota?

- 3) Hypothesis 3: There is a positive correlation between socio-technical design principles and increased productivity.
- Research Question 3: Is there a positive correlation between socio-technical design principles and increased productivity?
	- 4) Hypothesis 4: Organizational learning will have a significantly positive correlation to achieving a reduced daily work hour goal.

Research Question 4: Will organizational learning have a significantly positive correlation to achieving a reduced daily work hour goal?

5) Hypothesis 5: Responsible autonomy has a significantly positive correlation to the promotion of productivity and innovation.

Research Question 5: Will responsible autonomy have a significantly positive correlation to the

promotion of productivity and innovation?

6) Hypothesis 6: Responsible autonomy has a significantly positive correlation to organizational learning among regional manufacturers.

Research Question 6: Will responsible autonomy have a significantly positive correlation to organizational learning among regional manufacturers?

Figure 9. Socio-technical Research Framework

3.3. Research Design

The research study design is non-experimental and qualitative investigation that conducted survey sampling to describe multi-level employee perceptions of socio-technical systems design and digital maturity within an organization. Evidence demonstrated that socio-technical readiness can be assessed through a survey-based research methodology (Wahbeh et al., 2019). In behavioral and social sciences Likert scales are often used to measure participant perceptions (Choi, 2010). A five-level Likert Scales was used with the following response options: (1) *Extremely unlikely*, (2) *Somewhat Likely*, (3) *Neither likely nor unlikely*, (4) *Somewhat likely*, and (5) *Extremely likely.*

3.4. Target Population and Sample

The target population and sample provided a framework to allow for generalizability to be applied. This is defined as "the extension of research findings and conclusions from a study conducted on a sample population to the population at large" (Colorado State University, 2024). The target population of regional manufacturers from Minnesota and North Dakota held subsets of the sample. A descriptive summary of the target population and sample are provided in the following sections.

3.5. Population

The target participants in this socio-technical research study were employees from various employment levels within manufacturing firms located in Minnesota and North Dakota. The manufacturing industry is a leading sector in the implementation of Industry 4.0 (Setyaningsih et al., 2020). Gottlich, 2024 further reported that the manufacturing sector performed sluggishly over the last two years and is seeing a rise in the PMI recently (Gottlich, 2024). External environment

considerations may also influence the employee's perceptions of the firm's socio-technical system design.

3.6. Sample Study

Participants met the following criteria: (a) geographically located in North Dakota or Minnesota, (b) employed by a manufacturer, and (c) volunteer their time to provide survey feedback. Participant enterprise details were found from the author's LinkedIn networks, UsBizData.com, a ND Department of Commerce list of manufacturers, Impact Dakota, and the Minn-Dak Manufacturers Association.

3.7. IRB Approval/Exemption

The two survey studies involved human participation and therefore required Institutional Review Board (IRB) evaluations. A request for IRB exemption was submitted to the IRB at North Dakota State University (NDSU) along with a copy of questionnaire prior to disseminating both surveys. As well, an IRB exemption was submitted to the IRB at NDSU for the web scraping project. Upon review IRB at NDSU determined the following exemption statuses

- 1. Protocol No. IRB0004902, "A Survey of Current Organizational Design Practices",
- 2. Protocol No. IRB0004709, "A Survey of Current Organizational Design Practices",
- 3. Protocol No. IRB 0004961, "Web Scraping Research Study".

Relevant documents are furnished in the appendices in this research.

3.8. Data Collection

The survey was developed using Qualtrics at NDSU with the intent of collecting survey responses electronically. Qualtrics allowed for the distribution of surveys through social media, emails, and URL links. The online survey was anonymous. Data was captured for the individual responses from small, medium, and large enterprises in North Dakota and Minnesota. The data

was saved onto Excel spreadsheets. The software SAS 9.4 was used to read the data from the Excel spreadsheets directly using Proc IMPORT.

3.9. Data Validity

The internal consistency of the surveys was used to indicate the level of measuring the same construct. Cronbach's alpha statistical factor was calculated to measure the internal consistency of a group of items that are combined to create a single five-level Likert scale. Reliability coefficients of 0.70 or more are considered acceptable. The Cronbach alpha coefficients of the socio-technical system design elements among all industries met this threshold, which indicates the reliability of the survey scales in providing valid results (Aichouni et al., 2023).

3.10. Data Analysis

Once the data was imported into SAS, the Pearson and Polychoric correlation coefficients analyses were conducted using base SAS and SAS/STAT, which are components of the SAS version 9.4. The Pearson correlation was accessed utilizing the Proc CORR function and the Polychoric correlation coefficient were accessed with the Proc FREQ function (SAS Institute Inc., 2023). The *p*-value < 0.05 was considered significant. Both Polychoric and Pearson correlation coefficients have been used to analyze five-level Likert Scales. The is Polychoric correlation statistic is used for two discrete *ordinal* variables. "The polychoric correlation applies to any ordinal variable, including character variables with measurements levels such as "low", "medium", and "high" (SAS Institute Inc., 2023).

The five-level Likert Scale was used to collect insights on a variety of topics relevant to Industry 4.0 and socio-technical systems design. A five-level Likert Scale was used with the following five response options: (1) *Extremely unlikely*, (2) *Somewhat unlikely*, (3) *Neither likely* *nor unlikely*, (4) *Somewhat likely*, and (5) *Extremely likely*. The responses also include a continuous variable, which notes the degree in which the participant agrees or disagrees with the question. "Although rating and metrical scale data posess the same property of orders as the numbers in the real number system, ordinal data, unlike metrical data, lack the property of equal distances between units or categories. Given that Pearson's r requires metrical data, one must assume that equal distance exists among consecutive response categories in order to to warrant any meaningfulness of the correlation coefficients" (Choi, J., 2010). The assumption of linearity addresses the distance between each level of the Likert scale and assumes that the distance between "*Extremely unlikely*" and "*Somewhat Likely*" are the same distance as between "*Somewhat likely*" and "*Extremely likely*". As well, the distances of both sets of Likert levels should be equal to "*Neither likely nor unlikely*" (Lalla, M., 2017).

Pearson correlation coefficient is defined by SAS as "The Pearson product-moment correlation is a parametric measure of association for two variables. It measures both the strength and the direction of a linear relationship. If one variable *X* is an exact linear function of another variable *Y*, a positive relationship exists if the correlation is 1 and a negative relationship exists if the correlation is –1. If there is no linear predictability between the two variables, the correlation is 0. If the two variables are normal with a correlation 0, the two variables are independent. However, correlation does not imply causality because, in some cases, an underlying causal relationship might not exist" (SAS Institute Inc., 2023).

The Pearson correlation coefficient formula per SAS is noted in the equation below, "where \bar{x} is the sample mean of *x* and is the sample mean of *y*". Also, where r is equal to the correlation coefficient, x_i is the values of the x-variables in a sample, \bar{x} is the mean of the values

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of the x-variable, y_i are the values of the y-variable in a sample, and \bar{y} is the mean of the values of the y-variables (SAS Institute Inc., 2023).

$$
r_{xy} = \frac{\sum_{i} \left((x_i - \bar{x})(y_i - \bar{y}) \right)}{\sqrt{\sum_{i} (x_i - \bar{x})^2 \sum_{i} (y_i - \bar{y})^2}} \tag{1}
$$

Equation 1. Pearson Correlation Coefficient as Provided by SAS Institute Inc.

The Pearson r coefficient was used in the study to indicate whether a significant correlation existed among the socio-technical constructs, as well as, factors of increased productivity, reduced daily work hour goals, and Industry 4.0 integration. The findings in this study may benefit manufacturers in the region in which the study occurred as well as other manufacturers in surrounding communities through leading to organizational improvements in socio-technical readiness to advance strategic planning to invest in Industry 4.0 and realize predictive results, such as reduced daily work hour goals and increased productivity. Studies have used the Pearson correlation coefficient to test the statistical significance of surveys issued using a five-level Likert Scale (Holden, R., 2019).

Pearson's correlation coefficient measures continuous data on an interval scale, such as the Likert Scale responses. The assumption is that surveys were received from multi-levels of employee perspectives, such as being management and employee-rated responses. This supported the research questions of this study. Pearson's correlation coefficient measures the linear relationship between two random variables to determine the strength of the correlation (Ly, Marsman, & Wagenmakers, 2019).

The Polychoric correlation coefficient is defined in the SAS manual as "Polychoric correlation estimates the Pearson correlation between two continuous variables that underlie the ordinal variables. As mentioned in the previous section, an ordinal variable, Y, can be thought of as a discretization (or *binning*) of an underlying unobserved continuous variable, X. The

unobserved variable is called a *latent variable*. Even if the ordinal variables are character variables, the underlying variables are numeric, which means that they can be standardized. Polychoric correlation assumes that the latent variables are bivariate normal with correlation ρ. The polychoric correlation is defined as the estimate of ρ. That is, when we say that the polychoric correlation between two ordinal variables, Y1 and Y2, is *r*, it means that *r* is an estimate for the Pearson correlation between two latent variables, X1 and X2, that are bivariate normal and that are inferred from Y1 and Y2." (SAS Institute Inc., 2023)

The methods used to conduct the polychoric correlation coefficient analyses using base SAS and SAS/STAT, which are components of SAS version 9.4, utilized the methods cited in Drasgow, 1986 and Olsson, 1979. These citations are provided in the SAS manual (SAS Institute, Inc., 2023).

The Polychoric correlation function first computes the thresholds of the variables from the results of the Likert Scale responses to create a frequency table. Next the thresholds are computed, and the values are used to evaluate the log likelihood of possible values of the Polychoric correlation. The Polychoric correlation is used to compute the conditional probability of the observed responses. "Polychoric correlations are not computed using a closed-form equation, one can iterate across different possible correlations to find the values that maximize the log of likelihood" (Kite, 2024).

"Polychoric correlation measures the correlation between two unobserved, continuous variables that have a bivariate normal distribution. Information about each unobserved variable is obtained through an observed ordinal variable that is derived from the unobserved variable by classifying its values into a finite set of discrete, ordered values" (Drasgow, 1986) (Olsson, 1979).

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"The polychoric correlation coefficient is the maximum likelihood estimate of the productmoment correlation between the underlying normal variables. The range of the polychoric correlation is from –1 to 1. Olsson gives the likelihood equations and the asymptotic standard errors for estimating the polychoric correlation. The underlying continuous variables relate to the observed ordinal variables through thresholds, which define a range of numeric values that correspond to each categorical level. PROC CORR uses Olsson's maximum likelihood method for simultaneous estimation of the polychoric correlation and the thresholds" (SAS Institute Inc., 2023). The Polychoric correlation method for the analyses with base SAS and SAS/STAT, which are components of the SAS version 9.4, used Olsson's maximum likelihood method of simultaneous estimates of the Polychoric correlations and the threshold. The maximum likelihood method is illustrated in the equations below. As well, a case study of Olsson's maximum likelihood method of simultaneous estimate is provided below (Olsson, 1979).

The dataset consists of an array of observed frequencies n_{ij} : $i = 1,2,..., s$; $j = 1,2,..., r$, as given in Table 1. If we denote by π_{ij} the probability that an observation falls into cell (i, j) , the likelihood of the sample is

$$
L = C \cdot \prod_{i}^{s} \prod_{j}^{r} \pi_{ij}^{n_{ij}}
$$
 (2)

Equation 2. Polychoric Maximum Likelihood Method of Simultaneous Estimate by Olsson, 1979

Where C is a constant. Taking logarithms,

$$
l = \ln L = \ln C + \sum_{i=1}^{s} \sum_{j=1}^{r} n_{ij} \ln \pi_{ij}
$$
\n(3)

Equation 3. Polychoric Maximum Likelihood Method of Simultaneous Estimate by Olsson, 1979

The thresholds for x are denoted by a_i , $i = 0, ..., s$ and the thresholds for y by b_j , $j = 0, ..., r$, where $a_0 = b_0 = -\infty$ and $a_s = b_r = +\infty$. It follows that

$$
\pi_{ij} = \Phi_2(a_i, b_j) - \Phi_2(a_{i-1}, b_j) - \Phi_2(a_i, b_{j-1}) + \Phi_2(a_{i-1}, b_{j-1})
$$

Where Φ_2 is the bivariate normal distribution function with correlation ρ .

The parameters to be estimated are ρ , $a_1 ... a_{s-1}$, $b_1 ... b_{r-1}$. Partial differentiation of *l* with respect to these parameters yields

$$
\frac{\partial l}{\partial \rho} = \sum_{i=1}^{s} \sum_{j=1}^{r} \frac{n_{ij}}{\pi_{ij}} \frac{\partial \pi_{ij}}{\partial \rho}
$$

$$
\frac{\partial l}{\partial a_k} = \sum_{i=1}^{s} \sum_{j=1}^{r} \frac{n_{ij}}{\pi_{ij}} \frac{\partial \pi_{ij}}{\partial a_k}
$$

$$
\frac{\partial l}{\partial b_m} = \sum_{i=1}^{s} \sum_{j=1}^{r} \frac{n_{ij}}{\pi_{ij}} \frac{\partial \pi_{ij}}{\partial b_m}
$$

Since $\partial \Phi_2(u, v) / \partial \rho = \phi_2(u, v)$ where ϕ_2 is the bivariate normal density function, (see Tallis,

1962, p 344; see also Johnson & Kotz, 1972, p44), it follows that

$$
\frac{\partial \pi_{ij}}{\partial \rho} = \phi_2(a_i, bj) - \phi_2(a_{i-1}, b_j) - \phi_2(a_i, b_{j-1}) + \phi_2(a_{i-1}, b_{j-1})
$$

Therefore, (5) may be written

$$
\frac{\partial l}{\partial \rho} = \sum_{i=1}^{s} \sum_{j=1}^{r} \frac{n_{ij}}{\pi_{ij}} \{ \phi_2(a_i, bj) - \phi_2(a_{i-1}, b_j) - \phi_2(a_i, b_{j-1}) + \phi_2(a_{i-1}, b_{j-1}) \}
$$

In (6), it is evident that

 $\partial\pi_{ij}$ ∂a_k = $\overline{\mathcal{L}}$ $\overline{1}$ \mathbf{I} \mathbf{I} \int_0^0 if $i \neq k$ and $i \neq k + 1$, i. e. if the formula for π_{ij} does not contain a_k $\partial \boldsymbol{\Phi}_2(a_k, b_j)$ ∂a_k $-\frac{\partial \boldsymbol{\Phi}_2(a_k, b_{j-1})}{\partial x_i}$ ∂a_k if $k=i$ $-\frac{\partial \boldsymbol{\Phi}_2(a_k, b_j)}{\partial x_j}$ ∂a_k $+\frac{\partial\Phi_2(a_k,b_{j-1})}{\partial x}$ ∂a_k $if k = i - 1$ (4)

Equation 4. Case 1: All Parameters are Estimated Simultaneously - Polychoric Maximum Likelihood Method of Simultaneous Estimate by Olsson, 1979

Thus, in (6) it suffices to let *i* go from *k* to $k + 1$. Therefore, (6) maybe written

$$
\frac{\partial l}{\partial a_k} = \sum_{j=1}^r \frac{n_{kj}}{\pi_{kj}} \left\{ \frac{\partial \Phi_2(a_k, b_j)}{\partial a_k} - \frac{\partial \Phi_2(a_k, b_{j-1})}{\partial a_k} \right\} + \frac{n_{k+1j}}{\pi_{k+1j}} \left\{ - \frac{\partial \Phi_2(a_k, b_j)}{\partial a_k} + \frac{\partial \Phi_2(a_k, b_{j-1})}{\partial a_k} \right\}
$$
\n
$$
= \sum_{j=1}^r \left(\frac{n_{kj}}{\pi_{kj}} - \frac{n_{k+1,j}}{\pi_{k+1,j}} \right) \left\{ \frac{\partial \Phi_2(a_k, b_j)}{\partial a_k} - \frac{\partial \Phi_2(a_k, b_{j-1})}{\partial a_k} \right\}
$$
\n(5)

Equation 5. Polychoric Maximum Likelihood Method of Simultaneous Estimate by Olsson, 1979

Also, if we let ϕ_1 and ϕ_1 denote univariate normal density and distribution function, respectively,

$$
\frac{\partial \boldsymbol{\Phi}_2(u,v)}{\partial u} = \phi_1(u). \boldsymbol{\Phi}_1\left\{ \frac{(v-\rho u)}{(1-\rho^2)^{1/2}} \right\}
$$

[Tallis,1962, p 346]. Equation (6) may now be written as

$$
\frac{\partial l}{\partial a_k} = \sum_{j=1}^r \left(\frac{n_{kj}}{\pi_{kj}} - \frac{n_{k+1,j}}{\pi_{k+1,j}} \right) \cdot \phi_1(a_k) \cdot \left[\boldsymbol{\Phi}_1 \left\{ \frac{\left(b_j - \rho a_k \right)}{\left(1 - \rho^2 \right)^{1/2}} \right\} - \boldsymbol{\Phi}_1 \left\{ \frac{\left(b_{j-1} - \rho a_k \right)}{\left(1 - \rho^2 \right)^{1/2}} \right\} \right]
$$

From the symmetry it also follows that

$$
\frac{\partial l}{\partial b_m} = \sum_{i=1}^{s} \left(\frac{n_{im}}{\pi_{im}} - \frac{n_{i,m+1}}{\pi_{i,m+1}} \right) \phi_1(b_m) \cdot \left[\Phi_1 \left\{ \frac{(a_i - \rho b_m)}{(1 - \rho^2)^{1/2}} \right\} - \Phi_1 \left\{ \frac{(a_{i-1} - \rho b_m)}{(1 - \rho^2)^{1/2}} \right\} \right]
$$

Equations (9), (13) and (14) constitute the set of first order derivatives of the log-likelihood.

We denote the sample size by N, and introduce the notation $\theta' =$ $(\rho, a_1, a_2, \ldots, a_{s-1}, b_1, b_2, \ldots, b_{r-1})$. The matrix $I_{(\theta)}$ of expected second order derivatives of l with respect to θ is obtained from

$$
\left[\mathbf{I}_{(\theta)}\right]_{m,n} = N \sum_{i=1}^{s} \sum_{j=1}^{r} \frac{1}{\pi_{ij}} \left(\frac{\partial \pi_{ij}}{\partial \theta_{m}}\right) \left(\frac{\partial \pi_{ij}}{\partial \theta_{n}}\right)
$$

[Tallis, 1962, p 348]. The derivatives within parenthesis in (19) are obtained from (8) and (10).

A large-sample estimate of the covariance matrix of θ is therefore

$$
V = \mathbf{I}_{(\theta)}^{-1} \tag{6}
$$

Equation 6. Case 1: Variance/Covariance - Polychoric Maximum Likelihood Method of Simultaneous Estimate by Olsson, 1979

A tetrachoric correlation coefficient analysis was conducted to assess the variables from ordinal and numerical values of the web scraping project to estimate the expected proportion of this ordinal and continuous data (Verhulst, 2021). "If both ordinal variables have two levels, then the polychoric correlation is called the tetrachoric correlation. That is, tetrachoric correlation is used to analyze a 2 x 2 table of frequency count" (SAS Institute Inc., 2023).

$$
\Phi(h,k;\rho) = \left[2\pi(1-\rho^2)^{1/2}\right]^{-1} \int_{-\infty}^h \int_{-\infty}^k exp\left[-\frac{x^2 - 2\rho xy + y^2}{2(1-\rho^2)}\right] dxdy \tag{7}
$$

Equation 7. Tetrachoric Correlation Coefficient Provided by Olsson, 1979

The websites of 149 manufacturing firms located in the Minnesota and North Dakota regions was reviewed. Additionally, a patent review was conducted. The correlations of patent holders to the keywords used among Industry 4.0 were assessed with the tetrachoric correlation coefficient. The data was imported into SAS and analyses were conducted using base SAS and SAS/STAT, which are components of the SAS version 9.4. The tetrachoric correlation coefficient were accessed with the Proc FREQ function (SAS Institute Inc., 2023). The results of this study are found in Chapter 5.

3.11. First Survey

The purpose of the first qualitative survey was to capture the individual responses employees of small, medium, and large enterprises in North Dakota and Minnesota. The qualitative survey ascertained the level of socio-technical organizational design utilized and the implementation of Industry 4.0 among business sizes. Additionally, an outcome of productivity increases due to Industry 4.0, socio-technical design, and/or business size implementation was assessed. The questionnaire focused on the collection, analysis, summarization, testing, and iterating and amending of data among 24 small, medium, and large manufacturers in North

Dakota and Minnesota. As well, internal, and external organizational design with consideration of the socio-technical system framework was reviewed. Human-factor analysis of employee communication styles, multidisciplinary teams, and employee development were also assessed. The unit of analysis used in this research was the employees' opinions about the organizational changes observed using socio-technical theory. Random sampling from each business category was conducted in this anonymous study. Respondents represented small, medium, and large manufacturers. Thus, a variety of socio-economic contexts was sampled.

The research was designed by formulating the socio-technical research questions to discover human factors and requirements in the technology-centric Industry 4.0 context, determining the research design, designing a questionnaire in Qualtrics, collecting the data anonymously, analyzing and interpreting the data based on a combination of a five-level Likert Scale, open-ended questions, and defined multiple choice questions to prepare the assessment (Iacobucci, D. & Churchill, Jr., G, 2018). A five-level Likert Scales was used with the following response options: (1) *Extremely unlikely*, (2) *Somewhat Likely*, (3) *Neither likely nor unlikely*, (4) *Somewhat likely*, and (5) *Extremely likely.*

Participant enterprise details were found from the authors' LinkedIn networks, UsBizData.com, a ND Department of Commerce list of manufacturers, Impact Dakota, and the Minn-Dak Manufacturers Association. The online survey consisted of 25 questions, and one format of the survey was provided to all respondents to ensure consistency and comparability of the study.

Participant enterprise details were found from the authors' LinkedIn networks, UsBizData.com, Impact Dakota, and the Minn-Dak Manufacturers Association. The online survey consisted of 20 questions, and one format of the survey was provided to all respondents to ensure

the consistency and comparability of the qualitative study. The survey participants were anonymous. The geolocation of respondents was identified through using Qualtrics Survey software analytics. A five-level Likert Scale was used with the following five response options: (1) *Extremely unlikely*, (2) *Somewhat unlikely*, (3) *Neither likely nor unlikely*, (4) *Somewhat likely*, and (5) *Extremely likely*.

The online survey process was selected to streamline and expedite the informationgathering stage. The online survey link was sent through Qualtrics to approximately 750 small, medium, and large manufacturers. A total of 24 responses were received providing viable information over a period of approximately one month, yielding a response rate of 3%. Of the 24 respondent enterprises from North Dakota and Minnesota, there were 10 small, six medium-sized, and eight large manufacturers that responded from North Dakota and Minnesota. Small businesses were considered to have fewer than 50 employees; medium-sized businesses were considered to have between 50 and 250 employees; and large businesses were considered to have more than 250 employees.

3.12. Second Survey

The purpose of the second survey was to collect data anonymously from employees of regional manufacturers on the types of socio-technical organizational design practices implemented within the work organization that contribute to the achievement of a reduced daily work hour goal. The themes of the questions were organizational learning, responsible autonomy, communication strategy, reduced work hour goals, leadership characteristics, digital maturity, resource allocation, bottom-up problem solving, and socio-technical design. The survey included the use of an online qualitative survey to gather the individual responses of 35 small, medium, and large manufacturers in Minnesota and North Dakota.

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Random sampling from each business size was conducted in this anonymous study. A variety of socio-economic contexts was sampled. The unit of analysis used in this research was the participants' anonymous opinions about the socio-technical design employed within small-, medium-, and large-sized manufacturers. The survey was designed by formulating the research questions based on nine academic research articles, which are referenced in the 'Results' section, on topics relevant to technology, processes, culture, people, infrastructure, and goals, which are integral to a socio-technical design framework.

The anonymous questionnaire was designed using Qualtrics. The analysis and interpretation of the data was based on a combination of a five-level Likert scale, open-ended questions, and defined multiple choice questions to prepare the assessment [47]. A five-tiered Likert scale was utilized that allowed for the responses of: (1) *Extremely Unlikely*, (2) *Somewhat Unlikely*, (3) *Neither Likely nor Unlikely*, (4) *Somewhat Likely*, and (5) *Extremely Likely*.

Participants were reached through the authors' LinkedIn networks, UsBizData.com (accessed on), an ND Department of Commerce list of manufacturers, Impact Dakota, and the Minn-Dak Manufacturers Association. The questionnaire provided 25 questions, and one format of the survey was provided to the public.

The online survey process was selected to streamline and expedite the informationgathering stage. The online survey link was sent through Qualtrics to approximately 2500 small, medium, and large manufacturers. A total of 35 responses were received providing viable information over a period of approximately one month, yielding a response rate of 1.4%. Small businesses were considered to have fewer than 50 employees; medium-sized businesses were considered to have between 50 and 250 employees; and large businesses were considered to have more than 250 employees.

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3.13. Ethical Considerations

The employee perspectives shared were considered the opinions regarding organizations. A voluntary consent statement was provided to information the participant that they are willingly able to complete the surveys. The research procedures provide accessibility to complete the surveys confidentially and anonymously through an embedded link generated through Qualtrics. The data was collected and stored by Qualtrics' online database system. The research surveys were reviewed and approved by North Dakota State University's IRB.

3.14. Summary

The third chapter provided information on the purpose of the study, research design, target population sample, population information, sample study, IRB approval and exemption, data collection, data validity, data analysis, and ethical considerations. The quantitative research study explored the socio-technical readiness and digital maturity through multi-levels of employee perspectives from manufacturers in Minnesota and North Dakota. Chapter 4 provides the results of this research study.

4. RESULTS

4.1. Results for Manufacturers – First Survey

In the first survey it was stated upfront in the message sent to respondents that anonymity and confidentiality would be ensured. Pearson correlation coefficients were used to check the pairwise linear relationships. The relationships tested were among the socio-technical constructs, Industry 4.0 integration, productivity increases, and business sizes of manufacturers surveyed in North Dakota and Minnesota.

The manufacturing businesses were assessed for the current state of socio-technical design in manufacturing setting and Industry 4.0 integration. The manufacturing industry was assessed for the Minnesota and North Dakota markets only. In Minnesota there were four (4) mediumsized businesses and two (2) large businesses that responded. In North Dakota, there were 18 manufacturing businesses with ten (10) representing small businesses, two (2) representing medium-sized businesses, and six (6) representing large businesses.

The following questions were posed and pertain to the first socio-technical construct of Data Gathering.

- How likely is your organization to gather relevant data from appropriate sources to assist in predicting solutions for integrating digital technology? (This was question 3: Q3.)
- How likely is your organization to systematically consider the relationships between internal and external factors to identify the contingencies and direction of relationships? (Q7)
- How likely is your organization to consider that a given end state or result may be reached by many potential means with each of an organization's six dimensions of goals, people, buildings/infrastructure, technology, culture, and process/procedures? (Q14)

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The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota businesses in the manufacturing industry for the first question were 83.3% and 77.77%, respectively. Similar Likert responses for the second question on the first socio-technical construct of Data Gathering for Minnesota and North Dakota were 66.66% and 72.22%, respectively. Similar Likert responses for the third question on the first socio-technical construct of Data Gathering for Minnesota and North Dakota were 83.33% and 8.33%, respectively.

The following questions were posed and pertain to the second socio-technical construct of Analysis and Interpretation.

- How likely is your organization to analyze and classify data collected in your organization to support organizational design? (Q4)
- How likely is your organization to consider the implication of the external environment as it relates to the organizational design? (Q6)
- How likely is your organization to engage in self-inspection to identify the origin of variance? (Q14)

The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota businesses in the manufacturing industry for the first question were 66.67% and 72.22%, respectively. Similar Likert responses for the second question on the second socio-technical construct of Analysis and Interpretation for Minnesota and North Dakota were 50% and 72.22%, respectively. Similar Likert responses for the third question on the second socio-technical construct of Analysis and Interpretation for Minnesota and North Dakota were 66.67% and 77.78%, respectively.

The following questions were posed and pertain to the third socio-technical construct of Summarizing the Findings.

- How likely is your organization to identify and group key system factors using visual aids, such as infographics? (Q5)
- How likely is your organization to generate key inferences regarding the system and how it works to support predictive work? (Q11)

The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota businesses in the manufacturing industry for the first question on the third socio-technical construct of Summarizing the Findings were 83.33% and 55.56%, respectively. Similar Likert responses to the second question on the third socio-technical construct

for MN and ND, were 83.33% and 66.66%, respectively.

The following questions were posed and pertain to the fourth socio-technical construct of Testing the Results with Stakeholders.

- How likely is your organization to visually consider internal and external dimensions of the work organization to assess underexplored or related areas? (Q7)
- How likely is your organization to include feedback or test analysis from key stakeholders for accuracy, omissions, and interpretations in the organizational design process? (Q9)
- How likely is your organization to diversify the resources utilized among various dimensions by supervisors, technicians, and managers? (Q16)
- How likely is your organization to allow for the employee growth through organizational design without peer pressure to support high-quality work? (Q18)

The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota businesses in the manufacturing industry for the first question on the fourth socio-technical construct of Testing the Results with Stakeholders were 83.33% and 61.11%, respectively. Similarly, Likert responses to the second question on the fourth sociotechnical construct for Minnesota and North Dakota were 50% and 55.55%, respectively. Similar Likert responses to the third question on the fourth socio-technical construct for Minnesota and North Dakota were 83.33% and 66.66%, respectively. Similar Likert responses to the fourth question on the fourth socio-technical construct for Minnesota and North Dakota were 66.66% and 61.11%, respectively.

The following questions pertain to the fifth socio-technical construct of Iterating and Amending as Necessary.

- How likely is your organization to modify the organizational design process after discussion? (Q10)
- How likely is your organization to design information systems to provide information in the first place when action is needed? (Q17)
- How likely is your organization to task multidisciplinary teams to continuously evaluate and review the work system design process? (Q19)
- How likely is your organization to add any relevant factors to the organizational design that emerge from the data during analysis or following previous steps? (Q20)

The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from

Minnesota and North Dakota businesses in the manufacturing industry for the first question on the fifth socio-technical construct of Iterating and Amending as Necessary were 66.67% and 83.33%, respectively. The similar Likert responses to the second question on the fifth socio-technical construct for Minnesota and North Dakota were 100% and 72.22%, respectively. Similar Likert responses to the third question on the fifth socio-technical construct for Minnesota and North

Dakota were 83.33% and 66.66%, respectively. Similar Likert responses to the fourth question on the fifth socio-technical construct for Minnesota and North Dakota were 66.67% and 72.22%, respectively.

Question 12 addressed Industry 4.0 specifically. It read, "How likely is your organization to align the organizational design with Industry 4.0 integration?". The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota were 16.67% and 38.89%, respectively.

Question 21 addressed the variable of productivity. It read, "How likely is your organization to observe increased productivity per employee due to the implementation of organizational design?" The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota were 50% and 33.33%, respectively.

The tables are organized with the top numbers being the Pearson's correlation coefficient and the lower numbers the p-values. The null hypothesis between the variables was zero.

Table 4 displays the outcomes of all 24 manufacturers surveyed in Minnesota and North Dakota. The table measures socio-technical constructs, which are noted as C1 through C5, Industry 4.0 integration (Q12), productivity increases (Q21), and small, medium, and large business sizes (Q1). A strong and positive Pearson's correlation coefficient is observed among the five socio-technical constructs (C1-C5) and Industry 4.0 integration (Q12). A negative relationship was observed among Data Gathering (C1), Analysis and Interpretation (C2), Testing (C4), Iterating and Amending as Necessary (C5), and Increased Productivity (Q21). A weak, positive relationship was observed between Summarization (C3) and Increased Productivity (Q21). A positive relationship was observed between (C4) Testing and (C5) Iterate and Amend. A weak, positive relationship was observed among (C1) Data Gathering, (C2) Analysis and

Interpretation, and (Q1) business size. A strong positive, correlation exists among the five sociotechnical constructs C1 through C5, solely. Aggregately, the business size (Q1) had either a weak, positive or negative correlation to socio-technical constructs (C1–C5). One small manufacturer from North Dakota responded affirmatively on the Likert scale to Industry 4.0 integration (Q12) and Increased Productivity (Q21). Additionally, Testing the Results with Stakeholders (C4) appeared to have a less robust positive correlation with Data Gathering (C1), Analysis and Interpretation (C2), and Summarization (C3). Moreover, Iterating as Necessary had a less robust positive correlation with Data Gathering (C1) and Analysis and Interpretation (C2). Further, a negative correlation between Industry 4.0 integration (Q12) and increased productivity (Q21) existed. Aggregately, the business size had either a weak, positive, or negative correlation to socio-technical constructs. One small manufacturer from North Dakota responded affirmatively on the Likert scale to both questions.

Table 4. All Minnesota and North Dakota Manufacturers Surveyed

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Table 5 displays the 10 responses to integrating Industry 4.0 by small manufacturing businesses in North Dakota and Minnesota. A weak, positive relationship between Industry 4.0 integration (Q12) and Increased Productivity (Q21) was observed. A strong, positive correlation between the socio-technical constructs of C1 through C5 and Industry 4.0 integration (Q12) was observed. Of the five socio-technical constructs, Analysis and Interpretation (C2) and Testing (C4) correlated the least positively with Industry 4.0 integration (Q12). A strong, positive correlation among the socio-technical constructs of C1 through C5 was observed. A weak, positive correlation between Summarization (C3) and Increased Productivity (Q21) was observed. One small manufacturer from North Dakota responded affirmatively to both Industry 4.0 integration (Q12) and Increased Productivity (Q21) survey questions.

Table 5. Small Manufacturers in Minnesota and North Dakota Integrating Industry 4.0 (Q12)

Table 6 displays the six responses to integrating Industry 4.0 by medium-sized manufacturing businesses in North Dakota and Minnesota. A negative relationship was observed between Industry 4.0 integration (Q12) and increased productivity (Q21). A strong, positive correlation among Data Gathering (C1), Analysis and Interpretation (C2), Testing (C4), Iterating and Amending as necessary (C5), and Industry 4.0 integration (Q12) existed. A strong positive correlation among all socio-technical constructs with the exception of a moderate positive correlation between Data Gathering (C1) and Summarization (C3) was observed. A negative relationship among C1, C2, C4, and C5 constructs and Increased Productivity (Q21) existed. A weak, positive relationship with Summarization (C3) and Increased Productivity (Q21) existed.

Table 6. Medium-sized Manufacturers in Minnesota and North Dakota Integrating Industry 4.0 (Q12)

Table 7 displays the eight responses to integrating Industry 4.0 by large manufacturing businesses in North Dakota and Minnesota. A strong negative correlation between Industry 4.0 integration (Q12) and Increased Productivity (Q21) existed. A neutral relationship between Iterating and Amending as necessary (C5) and Increased Productivity (Q21) existed. A negative relationship among C2, C3, C4, and Increased Productivity (Q21) existed. A weak, positive relationship between Data Gathering (C1) and Increased Productivity (Q21) existed. A moderate, positive relationship between Data Gathering (C1) and Industry 4.0 integration (Q12) existed. A strong, positive correlation among all socio-technical constructs with the exception of a moderate, positive relationship between Data Gathering (C1) and Iterating and Amending as necessary (C5) existed. A strong, positive correlation between C2 through C5 and Industry 4.0 integration (Q12) existed.

Table 7. Large Manufacturers in Minnesota and North Dakota Integrating Industry 4.0 (Q12)

Table 8 displays the responses of the six manufacturers in Minnesota with regards to Industry 4.0 integration, increased productivity, and socio-technical constructs. A strong, negative correlation between Industry 4.0 integration (Q12) and Increased Productivity (Q21) existed. A strong, positive correlation was observed among all socio-technical constructs with the exception of the linear relationship between Summarization (C3) and Testing (C4), in which a moderate positive correlation was observed. A strong, positive correlation between C1, C2, C4, and C5 and Industry 4.0 integration (Q12) existed. A moderate, positive correlation between Summarization (C3) and Industry 4.0 integration (Q12) existed. A negative correlation between C1 through C5 and Q21 increased productivity existed.

Table 8. Minnesota Manufacturers Surveyed

Table 9 displays the relationship among socio-technical constructs, Industry 4.0 integration, and increased productivity among 18 manufacturers in North Dakota. A strong, positive correlation among all socio-technical constructs, C1 through C5, and Industry 4.0 integration (Q12) existed. The least positive socio-technical construct correlation was Industry 4.0 integration (Q12) was Analysis and Interpretation (C2). A strong, positive correlation among all socio-technical constructs solely existed. A negative correlation between C1 through C5 sociotechnical constructs and increased productivity (Q21) existed. A weak, positive correlation between Industry 4.0 integration (Q12) and increased productivity (Q21) existed.

Table 9. North Dakota Manufacturers Surveyed

Table 10 displays the relationship between Q3 on gathering relevant data from appropriate sources to assist in predicting solutions for integrating digital technology and Q12 on Industry 4.0 integration for manufacturers of all sizes. Eight (8) companies of all sizes out of 24 showed a positive correlation between gathering relevant data from appropriate sources to assist in predicting solutions for integrating digital technology and aligning the organizational design with Industry 4.0 integration. Table 11 highlights the Pearson and Polychoric Correlation Coefficients for Q3 by Q12 for all MN and ND manufacturers. The Pearson Correlation Coefficient value is .5314 and the Polychoric Correlation Coefficient value is .6378, which indicates a positive correlation. There is room for growth and improvement. Table 12 highlights the relationship between Q3 and Q21 on increased productivity for all MN and ND manufacturers. Four (4) companies of all sizes out of 24 manufacturers showed a positive correlation between gathering relevant data from appropriate sources to assist in predicting solutions for integrating digital technology and observing increased productivity per employee due to the implementation of organization design. Table 13 assesses the Pearson and Polychoric Correlation Coefficients for Q3 and Q21. Both Pearson and Polychoric values indicate a negative correlation for Q3 and Q21. Table 14 indicates the relationship between Q12 and Q21 for all MN and ND manufacturers. One (1) company illustrated a positive correlation between Industry 4.0 integration and increased productivity. Table 15 highlights the Pearson and Polychoric Correlation Coefficients for Q12 on Industry 4.0 integration and Q21 on increased productivity. The Pearson and Polychoric Correlation Coefficients indicate a negative correlation between Industry 4.0 integration and increased productivity.

Table of Q3 by Q12							
Q3(How likely is your organization to gather relevant data from appropriate sources to assist in predicting solutions for integrating digital technology?)	Q12(How likely is your organization to align the organizational design with Industry 4.0 integration?)						
Frequency Row Pct	1	$\overline{2}$	3	4	5	Total	
1	1 50.00	50.00	$\mathbf{\Omega}$ 0.00	0 0.00	0 0.00	2	
$\overline{2}$	Ω 0.00	0 0.00	2 100.00	0 0.00	θ 0.00	2	
3	0 0.00	0 0.00	100.00	0 0.00	∩ 0.00		
4	11.11	11.11	4 44.44	$\overline{2}$ 22.22	11.11	9	
5	θ 0.00	0 0.00	5 50.00	$\overline{2}$ 20.00	\mathcal{R} 30.00	10	
Total	$\overline{2}$	2	12	4	4	24	

Table 10. The relationship between Q3 and Q12 for MN and ND Manufacturers

Table 11. The Pearson and Polychoric Correlation Coefficients for Q3 by Q12 for MN and ND Manufacturers

Statistic	Value	ASE
Gamma	0.6444	0.1499
Kendall's Tau-b	0.4473	0.1234
Stuart's Tau-c	0.3776	0.1198
Somers' D C R	0.4508	0.1299
Somers' D R C	0.4439	0.1246
Pearson Correlation	0.5315	0.1302
Spearman Correlation	0.5094	0.1388
Polychoric Correlation	0.6378	0.1556
Lambda Asymmetric C R	0.0833	0.0798
Lambda Asymmetric R C	0.1429	0.0935
Lambda Symmetric	0.1154	0.0783
Uncertainty Coefficient C R	0.2475	0.0703
Uncertainty Coefficient R C	0.2627	0.0674
Uncertainty Coefficient Symmetric	0.2549	0.0662

Table of Q3 by Q21								
Q3(How likely is your organization to gather relevant data from appropriate sources to assist in predicting solutions for integrating digital technology?)	Q21(How likely is your organization to observe increased productivity per employee due to the implementation organizational design?)							
Frequency Row Pct	1	$\mathbf 2$	3	4	Total			
1	0 0.00	1 50.00	50.00	0.00	2			
$\overline{2}$	1 50.00	1 50.00	θ 0.00	$\mathbf{\Omega}$ 0.00	2			
3	0 0.00	0 0.00	0 0.00	100.00				
4	3 33.33	22.22	22.22	22.22	9			
5	5 50.00	0 0.00	3 30.00	2 20.00	10			
Total	9	4	6	5	24			

Table 12. The Relationship between Q3 and Q21 for MN and ND Manufacturers

Statistic	Value	ASE
Gamma	-0.0959	0.2265
Kendall's Tau-b	-0.0697	0.1653
Stuart's Tau-c	-0.0648	0.1532
Somers' D C R	-0.0725	0.1715
Somers' D R C	-0.0670	0.1593
Pearson Correlation	-0.0203	0.1610
Spearman Correlation	-0.0771	0.1982
Polychoric Correlation	-0.0943	0.2458
Lambda Asymmetric C R	0.1333	0.0878
Lambda Asymmetric R C	0.1429	0.0935
Lambda Symmetric	0.1379	0.0569
Uncertainty Coefficient C R	0.2104	0.0614
Uncertainty Coefficient R C	0.2204	0.0485
Uncertainty Coefficient Symmetric	0.2153	0.0546

Table 13. The Pearson and Polychoric Correlation Coefficients for Q3 by Q21

Table of Q12 by Q21								
Q12(How likely is your organization to align the organizational design with Industry 4.0 integration?)	Q21(How likely is your organization to observe increased productivity per employee due to the implementation organizational design?)							
Frequency Row Pct	1	$\mathbf{2}$	3	4	Total			
1	1 50.00	1 50.00	0 0.00	$\mathbf{\Omega}$ 0.00	2			
$\overline{2}$	0 0.00	Ω 0.00	50.00	50.00	$\overline{2}$			
3	$\overline{4}$ 33.33	$\overline{2}$ 16.67	3 25.00	3 25.00	12			
$\overline{\mathbf{4}}$	25.00	0 0.00	2 50.00	25.00	4			
5	3 75.00	1 25.00	0 0.00	0 0.00	$\overline{4}$			
Total	9	4	6	5	24			

Table 14. The relationship between Q12 by Q21 for all MN and ND Manufacturers

Statistic	Value	ASE
Gamma	-0.2466	0.2222
Kendall's Tau-b	-0.1779	0.1613
Stuart's Tau-c	-0.1667	0.1517
Somers' D C R	-0.1837	0.1655
Somers' D R C	-0.1722	0.1578
Pearson Correlation	-0.1876	0.1854
Spearman Correlation	-0.2144	0.1919
Polychoric Correlation	-0.2440	0.2279
Lambda Asymmetric C R	0.1333	0.1241
Lambda Asymmetric R C	0.0000	0.0000
Lambda Symmetric	0.0741	0.0691
Uncertainty Coefficient C R	0.2077	0.0577
Uncertainty Coefficient R C	0.2049	0.0445
Uncertainty Coefficient Symmetric	0.2063	0.0500

Table 15. The Pearson and Polychoric Correlation Coefficients for Q12 by Q21

Individual scatter plots of the socio-technical constructs of Data Gathering (C1), Analysis and Interpretation (C2), Summarization (C3), Testing (C4), and Iterate and Amend (C5) on the *x*axis and Industry 4.0 (Q12) on the *y*-axis were created for the manufacturing firms surveyed. These are illustrated in Figures 10-14 below. The three lines are the simple linear regressions for small, medium, and large companies. The linear regression highlights positive slopes for all three business sizes, indicating that, as Industry 4.0 integration increases, the socio-technical constructs are increasingly utilized within the work organization. In Figure 10, medium-sized companies integrating Industry 4.0 are more aligned with the socio-technical construct of Data Gathering than small and large companies. In Figure 11 the small companies integrating Industry 4.0 are more aligned early on with the socio-technical construct of Analysis and Interpretation than medium and large companies. Medium-sized companies are improving over time, perhaps due to being more equipped to apply these socio-technical techniques. Larger businesses do not seem to be as agile. In Figure 12 the larger companies integrating Industry 4.0 are more aligned with the socio-technical construct of Summarization. Figure 13 displays a positive correlation for all three business sizes integrating Industry 4.0 with the socio-technical construct of Testing. Large companies are doing better; however, the trend of medium companies is that they may surpass large and small companies. The data, however, is not available to support this conclusively. Figure 14 displays a positive correlation for all three business sizes that are integrating Industry 4.0 with the socio-technical construct of Iterate and Amend. Small and large companies are following the same slope. The trajectory for medium companies is more positive. Medium companies are more advanced in socio-technical system design and are responding uniquely in comparison. The medium companies may be more agile than large and have more resources than smaller companies in the region.

Figure 10. Data Gathering

Figure 11. Analysis and interpretation

Figure 12. Summarization

Figure 13. Testing

Figure 14. Iterate and Amend

4.2. Results for Manufacturers – Second Survey

In the second survey the adoption level of 22 Socio-technical practices was assessed using a five-point Likert scale or multiple-choice option. The first three questions were demographic and inquired about the business size based on the number of employees, the U.S. state in which the business is located, and the industry category, respectively. The survey assessed the current socio-technical organizational design practices and the motivation to adopt socio-technical work design, organizational learning, responsible autonomy, communication strategies, leadership skills, resource allocation, and flexible work arrangements conducive to implementing Industry

4.0. Out of the 35 manufacturers surveyed, 22 were small, seven (7) were medium, and six (6) were large that responded from Minnesota and North Dakota markets.

It was stated upfront in the message sent to respondents that anonymity and confidentiality would be ensured. Pearson and Polychoric correlation coefficients were used to check the pairwise linear relationships. As well, simple frequency charts and cross tabulation comparison charts were generated. The relationships tested were 22 socio-technical design practices grouped into six socio-technical constructs of people, culture, goals, technology, processes, and infrastructure.

The following questions were posed and pertain to the first socio-technical construct of Technology.

- Which digital maturity level best describes your current organization? The following options were provided and participants were limited to selecting one option – paper-based, spreadsheet, commercial or customized quality IT solutions, product lifecycle management software integrated (i.e. SAP, Oracle, and etc.), Highest level of digital maturity – closed-loop manufacturing, closed-loop quality data $\&$ product lifecycle management software integrated (Q4) (Dutta et al., 2021).
- How likely are employees to experience decision support through learning algorithms from various applications? (Q16) The following definition was provided, "Employee autonomy and decision-making are both impacted by learning algorithms in various IT applications. Algorithmic management can vary from decision support to judgment substitution for the employee. Learning algorithms shape the choices available to employees by automating decision-making, specifically by imposing predefined rules and by rapidly processing massive amounts of data" (Perez et al., 2022).

• In reference to the prior question, how likely are employees to experience judgment substitution for the employee through learning algorithms from various applications, such as software platforms, as an example? (Q17) (Perez et al., 2022)

The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota businesses for Q16 were 11.43% and 0%, respectively. Similar Likert responses for Q17 were 14.29% and 0%, respectively. In response to Q4, workflow processes indicated that eight (8) firms were paper-based, six (6) used spreadsheets, seven (7) leveraged commercial or customized quality IT solutions, eleven (11) used product lifecycle management software integrated only, and three (3) implemented close-loop manufacturing, closed-quality data, and product lifecycle management software that was integrated.

Q4 indicated that 20% of manufacturers that responded to the question were likely to establish a reduced daily work schedule or 14.29% of those surveyed. This response represents one (1) paper-based firm, two (2) firms utilizing spreadsheets, one (1) firm utilizing commercial or customized quality IT solutions, and one (1) firm leveraging product lifecycle management software integrated, and no firms using closed-loop manufacturing, closed-loop quality data, and product lifecycle management software integrated.

The following questions were posed and pertain to the second socio-technical construct of Processes.

• How likely is your organization to follow an operational process that includes these steps: data gathering, analysis and interpretation, summarizing the findings, testing the results with stakeholders, and iterating and amending as necessary to communicate recommendations to employees and stakeholders? (Q5) (Davis et al., 2014).

- How likely is your organization to create cross-functional diagrams, which are used to map the workflow of interrelated activities and resources (i.e. product, workers, machine, material, workstation setup, production line, factory operations, external factors, etc.) that transform inputs into outputs, as well as, to portray relationships among the various resources performing actions? (Q6) (Alsakka et al., 2023).
- Which timeline(s) does your organization generate, that include(s) key factors leading up to the event or scenario analyzed, grouped by the six factors of goals, people, buildings/infrastructure, technology, culture, and processes/procedures? The following options were provided and participants were allowed to select all that applied – longstanding (3+ months), issues immediately preceding the event (0-3 months), factors involved on the day, and the option to provide a customized response. (Q7) (Davis et al., 2014).
- How likely is your organization to continuously improve communication across departments and teams to instill employee engagement? (Q20) (Whiteoak, 2022).
- How likely is your organization to operate with standard operating procedures on work processes, systems architecture, and data formats? (Q23) (Enehaug, 2017).
- How likely is your organization to recognize both technology and people dimension to ensure that systems are highly efficient and contain better human characteristics that lead to better employee satisfaction? (Q25) (Sergei et al., 2023).

The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota businesses in the manufacturing industry for the Q5 were 25.71% and 20%, respectively. Similar Likert responses for Q6 were of the second socio-technical construct of Processes were 25.71% and 14.29%, respectively. Similar Likert responses for Q20 were 59.38% and 34.38%, respectively. Similar Likert responses for Q23 were 28.13% and 56.25%, respectively. Similar Likert responses for Q25 were 40.63% and 25%, respectively.

Responses for Q7 were as follows: 27.27% selected long-standing (3+ months) only, 9.09% selected long-standing (3+ months) and issues immediately preceding the event (0-3 months), 6.06% selected long-standing (3+ months), issues immediately preceding the event (0-3 months), and factors involved on the day, 27.27% selected issues immediately preceding the event (0-3 months) only, 3.03% selected issues immediately preceding the event (0-3 months) and factors involved on the day, 15.15% selected factors involved on the day. Seven participants provided a customized response. Responses included statements such as, "We use 3-month, 1 year, project specific, and long-term campaign strategy timelines" and "Some have a 1-3 month roll out, others 6-12 months".

The following questions were posed and pertain to the third socio-technical construct of Culture.

- How likely is your organization characterized by continuity and adaptation of work processes and human factors? (Q8) (Enehaug, 2017).
- How likely is your organization to promote the productivity and innovation of teams while minimizing conflicts? (Q9) (Enehaug, 2017).
- Productive organizational learning has three classifications. Which classification best describes the level of productive organizational learning in your work organization? The following options were provided and participants were able to make one selection: organizational inquiry that improves the way tasks are solved, inquiry in which the organization explores and restructures values and criteria for better performance, and
- inquiry that betters the organizational learning of both types 1 and 2. (Q11) (Enehaug, 2017).
- How likely is your organization engaged in a culture of organizational learning? The following definition was provided to participants, "Organizational learning is defined as organizational inquiry that improves the ways tasks are solved, in for better performance. Employees are creative, innovative, and willing to continuously learn and develop". (Q22) (Fischer et al., 2023).
- How likely would your organization be defined as organizationally flexible? The following definition was provided to participants, "Organizational flexibility is defined as relying on flexible structures, applying leadership skills, and organizing processes and projects based on agile teamwork". (Q24) (Sergei et al., 2023).

The combined Likert scale responses of Somewhat Likely and Extremely Likely from Minnesota and North Dakota businesses in the manufacturing industry for Q8 of the sociotechnical construct of Culture were 34.29% and 25.71%, respectively. Similar Likert responses for Q9 were 45.71% and 22.86%, respectively. As well, similar Likert responses for Q22 were 34.38% and 25%, respectively. Similar Likert responses for Q24 were 40.64% and 25%, respectively.

Responses for Q11 were as follows: 41.18% responded affirmatively to "organizational inquiry that improves the way tasks are solved", 11.76% responded affirmatively to "inquiry in which the organization explores and restructures values", and 47.06% responded affirmatively to "inquiry that betters the organizational learning of both types 1 and 2".

The following questions pertain to the fourth socio-technical construct of People.

- How likely is your organization to specify roles, responsibilities, and/or tasks that are specific to that job when you are trying to optimize or streamline a process? (Q10) (Enehaug, 2017).
- How likely is your organization to leverage a bottom-up problem-solving approach? The following example was provided to participants, "i.e. Job crafting that focuses on coworkers deciding and designing together to improve their work and workplaces during change". (Q18) (Whiteoak, 2022).
- How likely is your organization to develop cross-functional teams? (Q19) (Leso et al., 2022).
- How likely is your organization defined as engaging in responsible autonomy with employees and teams to achieve specific goals? The definition provided to participants was, "Responsible autonomy is defined as teams or groups having the discretion to judge and decide the organization, timing and pace of work tasks, which entails a relaxation of direct management supervision and helps to avoid 'silo thinking' by engaging the entire system". (Q21) (Fischer et al., 2023).

The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota businesses in the manufacturing industry for Q10 were 25.71% and 37.14%, respectively. Similar Likert responses for Q18 were 48.57% and 11.43%, respectively. Similar Likert responses for Q19 were 37.14% and 37.14%, respectively. Question 21 responses were 40.63% and 21.88%, respectively.

The following question pertains to the fifth socio-technical construct of Infrastructure.

• How likely is your organization to support allocation of resources and work to change and improve the production practices, organize work tasks, and strengthen internal cooperation? (Q12) (Enehaug, 2017)

The combined Likert scale responses of *Somewhat Likely* and *Extremely Likely* from Minnesota and North Dakota businesses in the manufacturing industry for Q12 were 37.14% and 31.43%, respectively.

The following questions pertain to the sixth socio-technical construct of Goals.

- How likely will establishing a reduced daily work hour goal serve as a way to jointly optimize the technical and human factors of your organization to achieve higher productivity and employee wellbeing? (Q13) (Enehaug, 2017)
- Are flexible working hours applied in activities upstream or downstream of the production system? The following examples were provided "i.e. design, protocoling, manufacturing, fabrication, testing, quality control, packaging, and shipping". The participants were provided with the option of responding 'yes' or 'no'. If a 'yes' reply was provided the participant was encouraged to provide a customized additional response to include further information. (Q14) (Cimini & Cavalieri, 2022)
- Are the hourly labor requirements and productivity goals achievable with a reduced hourly work week schedule when considering organizational factors? The following examples were provided "i.e. product-related or design-related factors, worker-related factors, material-related factors, factory operations-related factors, and production-line related factors". The participants were provided with the option of responding 'yes' or 'no'. If a 'yes' reply was provided the participant was encouraged to provide a customized

• additional response to include further information. (Q15) (Cimini, C. & Cavalieri, S., 2022)

The combined Likert scale responses of Somewhat Likely and Extremely Likely from Minnesota and North Dakota businesses in the manufacturing industry for Q13 were 14.29% and 5.71%, respectively.

The responses gathered for Q14 indicate that 48.57% responded 'yes' and 51.43% responded 'no'. The following customized responses were provided: 1) we are a brewery with a restaurant, taproom, and catering business. As long as the team communicates with each other and tasks get completed as scheduled, time is flexible. Restaurant has regular hours that we must maintain, but staff schedule time off as needed., 2) activity, 3) manufacturing and fabrication are flexed to accommodate jobs as necessary, 4) all work hours are flexible as long as the get their 40 hours in. 5) we are not a public based business, so hours can be flexible for our employees, 6) we have flexible work hours, up to a point. 7) Yes, for those types of support functions, very flexible working hours. The unwritten rule is that these functions should also put in a lot more time that 40 hrs/wk., and 8) Flexibility is more available in the downstream process. Chi-Square tests were completed for Q14 and a strong positive relationship was found with Q12, Q13, Q21 (responsible autonomy), Q24, and Q25. A T Test was constructed and illustrated a strong positive relationship between Q14 and the socio-technical constructs of Technology, Processes, Culture, People, and Goals.

The responses provided for Q15 indicate that 14.28% responded 'yes' and 85.72% responded no'. The following customized responses were provided: 1) delivery schedules, 2) Yes, we are struggling to keep employees busy with current workloads and 3) We can be flexible with hours, as needed.

The cross tabulations of Q15 and Q12 on allocation of resources indicated that three out of 35 manufacturers positively correlate. The cross tabulations for Q15 and Q13 on the reduced daily work hour goal indicated that four out of 35 manufacturers positively correlate. The comparison of Q15 and Q16 on learning algorithms indicated that one out of 35 manufacturers positively correlated. Comparing Q15 to Q17 on judgment substitution noted no correlation. Question 15 compared to Q18 on bottom-up problem-solving approach indicated five affirmative responses out of 35. Question 15 compared to Q19 on developing cross-functional teams illustrated an outcome of four positive correlations out of 35. Question 15 compared to Q20 on continuously improving communication achieved the outcome of six affirmative responses out of 32. Question 15 compared to Q21 on responsible autonomy indicated six positive responses out of 32. Question 15 compared to Q22 a culture of organizational learning illustrated three out of 32 positive correlations. Question 15 compared to Q23 on utilizing standard operating procedures indicated four positive correlations out of 32. Question 15 compared to Question 24 on organizational flexibility indicated six out of 32 positive correlations. Question 15 compared to Question 25 on socio-technical design and four positive observations were noted.

Chi-Square tests were completed for Q15 and a strong positive relationship was found with Q13, and Q21 (responsible autonomy). A T Test was constructed and showed a strong positive relationship between Q15 and the socio-technical constructs of Technology and Goals. The tables are organized with the top numbers being the Pearson's correlation coefficient and the lower numbers the p-values. The null hypothesis between the variables was zero. Tables 16-18 display the 32 viable outcomes resulting from the correlation between organizational learning and reduced daily work hour goals, responsible autonomy and the

promotion of productivity and innovation, and responsible autonomy and organizational learning among regional manufacturers.

Table 19 measures the socio-technical constructs of all manufacturers surveyed, which are noted as the technical subsystems of Technology, Processes, Infrastructure and social subsystems of Culture, People, and Goals. A strong and positive Pearson's correlation coefficient is observed between the following six relationships: Processes and Culture, Processes and People, Processes and Infrastructure, Culture and People, Culture and Infrastructure, and Infrastructure and People constructs. A moderate and positive relationship was observed between the following two relationships: Technology and Processes and Technology and Goals constructs.

The number of observations used for a pair of variables is the number that provided data for both variables in the pair. There is no other selection criterion for the Pearson Correlation Coefficient determination. Therefore, in the case of 31 observations in Table 19, as an example, there were four participants of the total 35 manufacturers that did not provide complete data for the socio-technical constructs in question.

The Pearson and Polychoric Correlation Coefficients indicate a negative correlation between Industry 4.0 integration and increased productivity. Tables 16 through 18 indicated the following items:

- Table 16 illustrates data collected from small manufacturers from MN and ND surveyed. Q13 on Reduced Daily Work Hours notes no significant relationship with Q18 (bottom-up communication), Q20 (communication across departments), Q21 (responsible autonomy), Q22 (organizational learning), and Q9 (promote productivity and innovation).
- Q18 has a positive correlation with Q20 and Q21.

- Q20 has a positive correlation also with Q22.
- Q9 has a positive correlation with Q22.
- Table 17 illustrates all medium-sized manufacturers from Minnesota and North Dakota surveyed. Q13 and Q21 have a positive correlation.
- Table 18 illustrates all large-sized manufacturers from MN and ND surveyed. No positive correlations were observed.

Figures 15 through 17 highlight the following outcomes:

- Fig. 15 illustrates that medium businesses are most engaged in responsible autonomy while engaging in a culture of organizational learning.
- Fig. 16 illustrates a slight positive slope for medium businesses on organizational learning and reduced daily work hour goal.
- Fig. 17 illustrates that small businesses only display a positive slope for responsible autonomy with promoting productivity and innovation.

Table 22 illustrates that for MN and ND production companies five out of 34 responded positively to Q15, which is assessing hourly labor requirements and productivity goals being achievable with a reduced daily work hour goal and the relationship to Q13 of the reduced daily work hour goal. Table 23 illustrates a positive Pearson and Polychoric Correlation Coefficient for Q15 to Q13.

Table 24 illustrates that for MN and ND production companies, 1 out of 34 responded affirmatively to a correlation between Q15 of hourly labor requirements and productivity goals being achievable with a reduced daily work hour weekly schedule when considering organizational factors and Q16 on productivity by learning algorithms. Table 25 did not show a significant Pearson Correlation Coefficient yet illustrated a significant Polychoric Correlation Coefficient.

Table 26 notes that seven (7) out of 34 responded affirmatively to Q15 on productivity to Q21 on responsible autonomy. Table 27 displays that no significant Polychoric and Pearson Correlation Coefficients assessing the relationship between Q15 and Q21 were observed. Table 28 displays all MN and ND manufacturers responses for the relationship between Q14 on flexible work hours and Q13 on reduced work hours. There were six (6) out of 34 responses in the affirmative. Table 29 highlights that the Pearson and Polychoric Correlations Coefficients on this relationship was not significant.

Table 30 illustrates the outcomes for all MN and ND manufacturers for the relationship between Q14 on flexible hours and Q16 on learning algorithms. Two out 34 manufacturers responded in the affirmative. Table 31 notes that the Pearson Correlation Coefficient is not significant, however, the Polychoric Correlation Coefficient is moderately significant.Table 32 reports that all MN and ND companies illustrate a affirmative response of 15 out of 34 for the relationship between Q14 flexible hours and Q16 learning algorithms. Table 33 illustrates no significance between this relationship with both correlation coefficient types.

Table 34 illustrates that 16 out of 34 MN and ND manufacturers responded affirmatively to the relationship between Q14 on flexible hours and Q21 on responsible autonomy. Table 35 shows a moderate significant Pearson Correlation Coefficient and significant Polychoric Correlation Coefficient Table 36 indicates that 16 out of 34 manufacturers responded affirmatively to the relationship between Q14 on flexible hours and Q24 organizational flexibility. Table 37 highlights a moderately significant Pearson Correlation Coefficient and a significant Polychoric Correlation Coefficient.

Pearson Correlation Coefficients, $N = 6$ $Prob > r $ under H0: Rho=0							
	Q13	Q18	Q20	Q ₂₁	Q22	Q ₉	
Q13 How likely will establishing a reduced daily work hour goal serve as a way to jointly optimize the technical and human factors of your organization to achieve higher productivity and employee wellbeing?	1.00000	-0.07495 0.8878	0.52145 0.2887	0.82268 0.0444	0.18210 0.7299	-0.42400 0.4021	
Q18 How likely is your organization to leverage a bottom-up problem-solving approach?	-0.07495 0.8878	1.00000	0.15811 0.7648	0.21437 0.6834	0.38651 0.4491	0.53033 0.2791	
Q20 How likely is your organization to continuously improve communication across departments and teams to instill employee engagement?	0.52145 0.2887	0.15811 0.7648	1.00000	0.54233 0.2663	0.76827 0.0743	0.44721 0.3739	
Q ₂₁ How likely is your organization defined as engaging in responsible autonomy with employees and teams to achieve specific goals?	0.82268 0.0444	0.21437 0.6834	0.54233 0.2663	1.00000	0.53029 0.2791	-0.24254 0.6433	
Q22 How likely is your organization engaged in a culture of organizational learning?	0.18210 0.7299	0.38651 0.4491	0.76827 0.0743	0.53029 0.2791	1.00000	0.62470 0.1848	
Q ₉ How likely is your organization to promote productivity and innovation of teams while minimizing conflicts?	-0.42400 0.4021	0.53033 0.2791	0.44721 0.3739	0.24254 0.6433	0.62470 0.1848	1.00000	

Table 17. All Medium-sized Manufacturers from Minnesota and North Dakota Surveyed

Table 18. All Large-sized Manufacturers from Minnesota and North Dakota Surveyed (Continued)

Pearson Correlation Coefficients $Prob > r $ under H0: Rho=0 Number of Observations								
	Technology	Processes	Culture	People	Infrastructure	Goals		
Technology	1.00000 32	0.38014 0.0319 32	0.20899 0.2592 31	0.15564 0.3950 32	0.06698 0.7157 32	0.47906 0.0055 32		
Processes	0.38014 0.0319 32	1.00000 32	0.79181 < .0001 31	0.77428 < .0001 32	0.68667 < .0001 32	0.18294 0.3162 32		
Culture	0.20899 0.2592 31	0.79181 < .0001 31	1.00000 31	0.79063 < .0001 31	0.66443 < .0001 31	-0.05447 0.7710 31		
People	0.15564 0.3950 32	0.77428 < .0001 32	0.79063 < .0001 31	1.00000 32	0.72450 < .0001 32	-0.10001 0.5860 32		
Infrastructure	0.06698 0.7157 32	0.68667 < .0001 32	0.66443 < .0001 31	0.72450 < .0001 32	1.00000 32	-0.03092 0.8666 32		
Goals	0.47906 0.0055 32	0.18294 0.3162 32	-0.05447 0.7710 31	-0.10001 0.5860 32	-0.03092 0.8666 32	1.00000 32		

Table 19. Socio-technical Construct Comparison of all Manufacturers Surveyed

Table 20 displays the relationship between digital maturity level and hourly labor requirements and productivity goals being achievable with a reduced hourly work week schedule when considering organizational factors. Three (3) out of 35 or 8.57% of businesses responded in the affirmative that utilized commercial or customized quality IT solutions or product lifecycle management software integrated into their operations. No businesses that utilized closed-loop manufacturing, closed-loop quality data & product lifecycle management software combined responded affirmatively. Significant to the design of cyber-physical systems, such as Digital twin, is closed loop interaction and control between human factors and smart communication and

information technologies (Guha et al., 2023). Product lifecycle management leverages big data, visual computing, horizontal and vertical integration, cyber-physical systems, supply chain and management, which brings the product closer to the customer leading to greater customization and supports value creation in the Industry 4.0 context (Sivananda et al., 2021). Product life cycle management is an integration process also known as "end-to-end" that is based on vertical and horizontal integrations and closely connects the customer, product design, and manufacturing

(Yao et al., 2021).

Table 20. Comparison of Digital Maturity Level (Q4) with Reduced Hourly Work Week Schedule (Q15)

Table 21 displays the relationship between the productive organizational learning type and responsible autonomy. A total of 31 manufacturers out of 35 responded to Questions 11 and 21. A total of 19 of 31 or 61% of responses were in the affirmative to describing the type of organizational learning that is or would be completed, as well as, engaging in responsible autonomy with employees and teams to achieve specific goals. As well, Tables 15-22 and Figures 27-29 provide additional information regarding the results of the second survey set.

Table 21. Comparison of Productive Learning type (Q11) to Responsible Autonomy (Q21)

Figure 15. Q21 Responsible Autonomy comparison to Q22 Organizational Learning

Figure 16. Q22 Organizational Learning Compared to Q13 Reduced Daily Work Hour Goal

Figure 17. Q21 Responsible Autonomy Compared to Q9 on Productivity and Innovation

Table 22. Minnesota and North Dakota Production Companies – Second Survey

Statistic	Value	ASE
Gamma	0.8851	0.0817
Kendall's Tau-b	0.5371	0.0913
Stuart's Tau-c	0.5329	0.1465
Somers' D C R	0.8148	0.0940
Somers' D R C	0.3540	0.0942
Pearson Correlation	0.6070	0.1178
Spearman Correlation	0.5912	0.1002
Polychoric Correlation	0.8128	0.1199
Lambda Asymmetric C R	0.1739	0.0790
Lambda Asymmetric R C	0.2857	0.2957
Lambda Symmetric	0.2000	0.1254
Uncertainty Coefficient C R	0.1733	0.0570
Uncertainty Coefficient R C	0.5042	0.1103
Uncertainty Coefficient Symmetric	0.2579	0.0764

Table 23. Pearson and Polychoric Correlation Coefficients for Q15 by Q13 – Second Survey

Table of Q15n by Q16							
Q15n(Are the hourly labor requirements and productivity goals achievable with a reduced hourly work week schedule when considering organizational factors?)		Q16(How likely are employees to experience decision support through learning algorithms from various applications?)					
Frequency Row Pct	$\mathbf{1}$	$\mathbf{2}$	3	4	Total		
N ₀	14 51.85	8 29.63	3 11.11	$\overline{2}$ 7.41	27		
Yes	Ω 0.00	3 42.86	3 42.86	14.29	7		
Total	14	11	6	3	34		

Table 24. Minnesota and North Dakota Production Companies – Second Survey
Statistic	Value	ASE
Gamma	0.7273	0.1427
Kendall's Tau-b	0.4089	0.1124
Stuart's Tau-c	0.3875	0.1336
Somers' D C R	0.5926	0.1409
Somers' D R C	0.2821	0.0984
Pearson Correlation	0.4065	0.1403
Spearman Correlation	0.4399	0.1198
Polychoric Correlation	0.6174	0.1864
Lambda Asymmetric C R	0.1500	0.0798
Lambda Asymmetric R C	0.0000	0.3499
Lambda Symmetric	0.1111	0.1361
Uncertainty Coefficient C R	0.1122	0.0462
Uncertainty Coefficient R C	0.2761	0.0859
Uncertainty Coefficient Symmetric	0.1596	0.0602

Table 25. Pearson and Polychoric Correlation Coefficients for Q15 by Q16 – Second Survey

Table 26. Minnesota and North Dakota Production Companies – Second Survey

Statistic	Value	ASE
Gamma	0.6124	0.1935
Kendall's Tau-b	0.2817	0.1066
Stuart's Tau-c	0.2734	0.1214
Somers' D C R	0.4180	0.1536
Somers' D R C	0.1899	0.0828
Pearson Correlation	0.3220	0.0938
Spearman Correlation	0.3086	0.1178
Polychoric Correlation	0.4916	0.2160
Lambda Asymmetric C R	0.0000	0.0000
Lambda Asymmetric R C	0.0000	0.0000
Lambda Symmetric	0.0000	0.0000
Uncertainty Coefficient C R	0.0728	0.0279
Uncertainty Coefficient R C	0.2055	0.0617
Uncertainty Coefficient Symmetric	0.1075	0.0376

Table 27. Pearson and Polychoric Correlation Coefficients for Q15 by Q21

Table 28. Minnesota and North Dakota Production Companies – Second Survey

Statistic	Value	ASE
Gamma	0.4643	0.2121
Kendall's Tau-b	0.2938	0.1418
Stuart's Tau-c	0.3599	0.1756
Somers' D C R	0.3611	0.1761
Somers' D R C	0.2391	0.1146
Pearson Correlation	0.3390	0.1481
Spearman Correlation	0.3234	0.1569
Polychoric Correlation	0.4345	0.1955
Lambda Asymmetric C R	0.0000	0.1230
Lambda Asymmetric R C	0.3125	0.2375
Lambda Symmetric	0.1282	0.1474
Uncertainty Coefficient C R	0.0645	0.0399
Uncertainty Coefficient R C	0.1381	0.0874
Uncertainty Coefficient Symmetric	0.0880	0.0547

Table 29. Pearson and Polychoric Correlation Coefficients for Q14n by Q13 – Second Survey

Table 30. Minnesota and North Dakota Production Companies – Second Survey

Statistic	Value	ASE
Gamma	0.5962	0.2009
Kendall's Tau-b	0.3756	0.1431
Stuart's Tau-c	0.4394	0.1668
Somers' D C R	0.4410	0.1671
Somers' D R C	0.3199	0.1234
Pearson Correlation	0.3687	0.1567
Spearman Correlation	0.4041	0.1536
Polychoric Correlation	0.5075	0.1898
Lambda Asymmetric C R	0.1500	0.1529
Lambda Asymmetric R C	0.3750	0.1849
Lambda Symmetric	0.2500	0.1457
Uncertainty Coefficient C R	0.0778	0.0567
Uncertainty Coefficient R C	0.1408	0.1022
Uncertainty Coefficient Symmetric	0.1002	0.0728

Table 31. Pearson and Polychoric Correlation Coefficients for Q14 by Q16 – Second Survey

Table 32. Minnesota and North Dakota Production Companies – Second Survey

Statistic	Value	ASE
Gamma	0.5882	0.2065
Kendall's Tau-b	0.3608	0.1393
Stuart's Tau-c	0.4152	0.1638
Somers' D C R	0.4167	0.1642
Somers' D R C	0.3125	0.1203
Pearson Correlation	0.3754	0.1520
Spearman Correlation	0.3918	0.1518
Polychoric Correlation	0.4912	0.1900
Lambda Asymmetric C R	0.0000	0.0000
Lambda Asymmetric R C	0.3750	0.1712
Lambda Symmetric	0.1875	0.0895
Uncertainty Coefficient C R	0.0668	0.0508
Uncertainty Coefficient R C	0.1299	0.0996
Uncertainty Coefficient Symmetric	0.0883	0.0672

Table 33. Pearson and Polychoric Correlation Coefficients for Q14 by Q18 – Second Survey

Table 34. Minnesota and North Dakota Production Companies Q14 by Q21 – Second Survey

Statistic	Value	ASE
Gamma	0.6842	0.1723
Kendall's Tau-b	0.4507	0.1284
Stuart's Tau-c	0.5398	0.1592
Somers' D C R	0.5417	0.1594
Somers' D R C	0.3750	0.1045
Pearson Correlation	0.5272	0.1250
Spearman Correlation	0.4936	0.1421
Polychoric Correlation	0.6325	0.1562
Lambda Asymmetric C R	0.0000	0.1489
Lambda Asymmetric R C	0.5000	0.1531
Lambda Symmetric	0.2286	0.1310
Uncertainty Coefficient C R	0.1273	0.0531
Uncertainty Coefficient R C	0.2642	0.1134
Uncertainty Coefficient Symmetric	0.1718	0.0722

Table 35. Pearson and Polychoric Correlation Coefficients for Q14 by Q21 – Second Survey

Table 36. Minnesota and North Dakota Production Companies Q14 by Q24– Second Survey

Statistic	Value	ASE
Gamma	0.7919	0.1324
Kendall's Tau-b	0.5080	0.1055
Stuart's Tau-c	0.6055	0.1355
Somers' D C R	0.6076	0.1354
Somers' D R C	0.4248	0.0836
Pearson Correlation	0.5644	0.1000
Spearman Correlation	0.5548	0.1179
Polychoric Correlation	0.7318	0.1298
Lambda Asymmetric C R	0.0000	0.0000
Lambda Asymmetric R C	0.4375	0.1555
Lambda Symmetric	0.2000	0.0745
Uncertainty Coefficient $\mathbf{C} \mathbf{R}$	0.1465	0.0467
Uncertainty Coefficient R C	0.2992	0.1055
Uncertainty Coefficient Symmetric	0.1967	0.0646

Table 37. Pearson and Polychoric Correlation Coefficients for Q14 by Q24 – Second Survey

5. WEB SCRAPING AND INNOVATION RESEARCH STUDY

The digital transformation of manufacturers is measured through the selection of transformation technology, the designed scope of work, and the subsequent results of the digital implementation. The increased use of digital technology in the manufacturing sector has produced positive results, such as fostering corporate innovation, reducing trade costs, optimizing resource allocation, optimizing organizational efficiencies and improving financial performance. Indirectly, digital transformation can reduce an organization's carbon emissions (Gao, 2023). At the microlevel of enterprises, a web scraping project was utilized as an accessible and inexpensive method of accessing web data to assess the digital maturity from a sample of Minnesota and North Dakota manufacturers that had been presented with both surveys (Speckmann, 2021). The keywords examined represent the nine fields of Industry 4.0, which are cyber-physical systems, the internet of things, big data, cyber security, cloud computing, additive manufacturing, advanced robotics, modelling and simulation, and augmented virtual reality. Through the methodology of web data extraction, this study reviewed a sample population of 149 websites of regional manufacturers. The data was reviewed through text analysis techniques to ensure the relevancy of the keywords to the project subject matter (Roth et al., 2024).

A recent keyword study found that the most frequently used terms associated with Industry 4.0 were 'design', 'management', 'internet', 'big data', 'system', 'model', and 'Industry 4.0'. Industry 5.0 is referred to through keywords as 'big data', 'system', 'design', or 'Industry 5.0' (Michulek and Gajanova, 2023).

Furthermore, a recent bibliometric analysis of keyword co-occurrence within the Industry 5.0 context was conducted by Ghobakhloo et al. The colors of the nodes represent the cooccurrence of keyword groups and the edges represent the limits or constraints of the bibliometric

study constructed by Ghobakhloo et al. The node sizes are scaled larger based on a greater number of connections and therefore are based on the importance in the study. Fig. 18 "implies that the literature associates several technologies with Industry 5.0, most notably AI and IoT. Sustainable development, man-made integration, and human-centric manufacturing are among the most acknowledged expected impacts of Industry 5.0. The Industry 5.0 literature pays particular attention to the issue of sustainability and efficiency in the energy context" (Ghobakhloo et al., 2023).

Figure 18. Bibliometric Analysis of Keyword Co-occurrence within Industry 5.0 Context from Ghobakhloo et al.

5.1. Background

The two surveys that were issued to regional manufacturers in Minnesota and North Dakota were very insightful, however, this is one dimension of a subjective depiction of a manufacturer's current operational status. This is where gathering data from manufacturers' websites is instrumental as this provides access to large amounts of structured data. A variety of manufacturing sectors were represented among the regional manufacturers assessed in the web scraping project. Small, medium, and large manufacturers are also represented (Roth et al., 2024).

5.2. Research Methodology

The Internet actively and consciously delivers broad information. The use of web scraping in research studies has steeply increased to greater than 2000 articles annually after 2019 (Mann, 2021). The research was conducted using manufacturer's websites as they are used to provide information on innovation, products, services, achievements, strategies, and relationships (Kinne & Lenz, 2021). The first task was to conduct a manual web scraping, which was conducted in a sample of 40 manufacturers' websites to assess the likelihood of adequate keyword representation within the large sample group of 149 manufacturers. The most prominent words characteristic to Industry 4.0 were listed during this first process. Afterwards, a keyword frequency analysis of the nine dimensions of Industry 4.0 was completed. The second task was to conduct the automated web scraping project, which included the output of web links and textual analysis reviewed.

The gathering of indirect data through the web scraping approach provides a method of assessing large amounts of data in an automated manner. Through web scraping, data collection is organized onto an Excel worksheet, which simplifies the analysis process. The information was collected from a variety of sources located on company websites, which may be from reports and blogs, as examples during a one-month period of November 1st through November 30th of 2023.

The collection of data was conducted in an ethical and legal manner, as it was cleared through North Dakota State University's Institutional Review Board (Speckmann, 2021). The web scraping software, Beautifulsoup from the open-source Python library designed for parsing HTML and XML documents. This tool facilitates the extraction of data from web pages by simplifying the process with its user-friendly methods for navigating the parse tree and locating specific elements. Diverse web scraping tasks are enabled through its adaptability to include data collection, content aggregation, and automated information retrieval. The use of this tool was utilized to ensure that certain security protocols were not bypassed and the collection of copywritten information was not conducted without authorization.

The web scraping initiative commenced by compiling website links of engineering and technological companies predominantly situated in the Fargo and Moorehead area. A total of 149 links to the companies' homepages were gathered for initial exploration. Subsequently, a request connection was employed incorporating appropriate header parameters such as User-Agent, Accept-Language, Accept-Encoding, and Connection, to establish effective interaction with each website. Following this, a Beautiful Soup object was initiated with the HTML data from the homepage and utilized an HTML tree parser for in-depth analysis. The Beautifulsoup Python software starts with the manufacturer's homepage, where the general information is located, and then downloads sub-webpages, where more specific information is hosted, for review. Employing an iterative approach, text data was systematically retrieved from all pages across the websites and archived the extracted information in a CSV file for further processing and analysis.

Data mining is leveraged to identify unique patterns in larger data sets. The data analysis phase commences with the preprocessing of raw data. Utilizing regular expressions punctuation marks, URLs, email addresses, emojis, and other non-essential elements are eliminated.

Subsequently, Natural Language Toolkit (NLTK) comes into play for segmenting the text into sentences and tokens, followed by the removal of stop words to refine the dataset further. Leveraging the resulting tokens, we calculate the frequency of each token present on the website of the corresponding company. These frequencies are then stored in a dictionary, with tokens serving as keys and frequencies as values. To discern which companies are spearheading technological advancements, the frequency of a predetermined list of keywords are tallied. The outcomes of this analysis are elucidated in the results section. The keywords are evaluated based on the semantic intent of the text retrieved was initiated. Thirty-three (33) keywords associated with the nine categories of Industry 4.0 were researched. The Git Hub link for the code is located at [https://github.com/alamincse32/WebScraping.git.](https://github.com/alamincse32/WebScraping.git) The number of words used for each keyword within each industry is illustrated in Table 40 below.

Lastly, an unknown innovation status among the regional manufacturers exists, therefore, a subsequent assessment of the number of patent holders among the manufacturers reviewed in the web scraping project was also conducted by cross-referencing the U.S. Patent and Trademark Office's online patent directory. Innovative organizations are flexible with the decision-making structure. Innovation is a significant catalyst to economic growth and therefore patents serve a key role. Innovation is defined as a new commercial application of progress outside of experimentation. The process of attaining an innovation is through the assessment and assembly of data, information, and knowledge that is creatively ordered and reordered to produce new knowledge. Organizations can secure patent protection from the U.S. Patent and Trademark Office, which provides patent protection to ensure monopoly profits and thereby creates substantial incentives to invest in new technologies (Shaffer et al., 2004).

The patent review did not exclude any date ranges and therefore may include product innovation, business process innovation, abandoned innovation activities, on-going innovation activities, and in-house or external research and development activities (Crjns et al., 2023). Approximately 37% or 55 manufacturers from the sample of 149 held patents. Digital transformation is more significant in regions with intellectual property protection and capitalintensive businesses (Gao, 2023).

5.3. Results

Preprocessing and language detection were completed, where web texts lacking relevant content were removed. The Beautifulsoup web scraping engine collected targeted data including the following manufacturer's information: (a) source URL and (b) text. The initial results identifying the keywords of the nine fields of Industry 4.0 are highlighted in Tables 38 and 40, as well as, Figures 20 through 26 below. Table 38 and Figure 20 display the five keywords associated with the first category of Cyber-physical systems. The number of manufacturers' websites utilizing each keyword are ranked as shown in Table 40.

Under the second category of Internet of Things, there were three (3) businesses leveraging the term 'IoT' on their respective websites. Figure 21 and Table 40 describe the third category of Big Data here the results indicate that two (2) manufacturers utilize 'big data' and seventy-four (74) utilize the keyword 'data'. Figure 22 and Table 40 also provide a review of the fourth category of 'Cyber Security' is displayed where two (2) manufacturers utilize 'cyber' and forty-eight (48) leverage the term 'compliance'. The fifth Cloud Computing category is also noted in Figure 23 and Table 40 and highlights the outcome of two (2) websites using the term 'cloud computing' and eighteen (18) utilizing the keyword 'cloud' (Roth et al., 2024).

Two keywords were searched under the sixth category of Additive Manufacturing as noted in Figure 24 and Table 40. The results for '3D printing' were five (5) manufacturers' websites leveraging this information. There were no websites found expressing the term '4D printing'. Table 40 displays the information for the seventh Advanced Robotics category, where nineteen (19) websites utilized the term 'robot', one (1) website presented the term 'advanced technology' and no (0) results were found for 'robot welders'. Figure 26 illustrates the eighth category of Modelling and Simulation, which resulted in the number of the keywords per manufacturer's website as shown in Table 40.

In the ninth category of Augmented Virtual Reality, only three (3) manufacturers' websites used the term 'virtual reality', which is also noted in Table 40.

A keyword search was also conducted for keywords related to Industry 4.0 and Industry 5.0. For the keyword 'sustainable', which is a core principle of Industry 5.0, twenty-four (24) manufacturers' websites described their businesses using this term. Figure 27 displays the keywords associated to the topic of Industry 4.0.

Nine Industry 4.0 Categories & Corresponding Keywords				
$1)$ Cyber-	2) Internet of	3) Big Data	4) Cyber	5) Cloud
Physical	Things		Security	Computing
Systems		Keywords:		
	Keyword:		Keywords:	Keywords:
Keywords:		Big Data, Data	Cyber,	
	IoT		Compliance	Cloud
automated,				Computing,
automation,				Cloud
detection, cyber				
physical,				
wearable				
devices				
6) Additive	7) Advanced	8) Modelling		
	Robotics	and Simulation	9) Augmented Virtual Reality	
Manufacturing				
Keywords:	Keywords:	Keywords:	Keyword:	
4D Printing,	Robot, Robot	Intellectual	Virtual Reality	
3D Printing	Welders.	Property, Digital		
	Advance	Twin, Research,		
	Technology	Design,		
		Development,		
		Testing		

Table 39. Industry 4.0 Categories and Keywords Searched in Web Scraping Project

Table 40. Number of Manufacturing Websites Using Keywords Associated with the Nine Industry 4.0 Categories

Table 40. Number of Manufacturing Websites Using Keywords Associated with the Nine Industry 4.0 Categories (Continued)

Dakota Manufacturers

Figure 20. Web Scraping Results for Keywords Associated with Cyber-physical Systems

Figure 21. Web Scraping Results for Keywords Associated with Big Data

Figure 22. Web Scraping Results for Keywords Associated with Cyber Security

Figure 23. Web Scraping Results for Keywords Associated with Cloud Computing

Figure 24. Web Scraping Results for Keywords Associated with Additive Manufacturing

Figure 26. Web Scraping Results for Keywords Associated with Modelling and Simulation

Figure 27. Web Scraping Results for Keywords Associated with Industry 4.0

5.4. Quantitative Analysis

Descriptive statistics, such as tetrachoric correlation, and also a frequency distribution analysis, were used to analyze the manufacturing websites that indicated each of the nine (9) Industry 4.0 categories (Norcross et al., 2020). A Tetrachoric Correlation was assessed to identify significant relationships between those manufacturers holding patents and Industry 4.0 keywords. According to this assessment, the keywords of 'Advanced Technology' and 'Big Data' had the most significant Tetrachoric Correlations with .9539 and .9841, respectively (Roth et al., 2024).

The frequency distribution analysis was also used to evaluate the current organizational design status of regional manufacturers in the Industry 4.0 and Industry 5.0 contexts. The quantitative analyses displayed that the Modelling and Simulation category of Industry 4.0 was the most prevalently communicated on websites and the Augmented Virtual Reality category of Industry 4.0 was the least communicated on websites.

5.5. Support of First and Second Survey Results

The purpose of the web scraping and innovation research study is to map the digital transformation through Industry 4.0 adoption and innovation and to support the results of the two qualitative surveys issued to the regional manufacturers in Minnesota and North Dakota requesting feedback on the current socio-technical design practices in the Industry 4.0 context. Through the results of the Industry 4.0 regional mapping, which considers regional socioeconomic conditions, we identify a picture of a "digital transformation divide" and more specifically an "IoT divide" among regional manufacturers, where IoT is fundamental to digital transformation (Russo et al., 2022). As indicated in the Literature Review chapter of this study, IoT and cloud computing are the least expensive and easiest technologies for SMEs to adopt. However, there is a low investment indicated in the web scraping results in both technology

categories. As an example, key products within the IoT sector are sensor technologies (Cotrino, A. et al., 2020). The first survey responses to Q12, which asks "How likely is your organization to align the organizational design with Industry 4.0 integration?" found eight (8) manufacturers or 33% responding affirmatively. There is minimal diversity of Industry 4.0 technologies used, which may indicate a support for the first surveys results.

Aggregately, in the first survey the socio-technical construct of 'Data Gathering' had significant correlations to all other socio-technical constructs. The significant level of representation of the keywords 'Data' and 'Big Data' from the web scraping project would appear to support the results of the first survey. The first survey also noted no significant correlation between 'Data Gathering' and 'Summarization' among medium-sized manufacturers in Minnesota and North Dakota, which may indicate that the appropriate Industry 4.0 technology are not fully integrated into the production design to realize productivity gains. As well, among largesized manufacturers 'Data Gathering' did not correlate significantly to 'Testing' and 'Iterate and Amend' socio-technical constructs. The question "How likely is your organization to design information systems to provide information where it is first needed?" was included in the 'Iterate and Amend' socio-technical construct. The lack of correlation to this inquiry indicates that technical solutions may not be fully integrated to assist with the interpretation of data throughout the entire workflow process.

The outcomes of the web scraping study confirm the results of the second survey, which indicated that among small manufacturers in Minnesota and North Dakota there may be significant gaps in technical knowledge acquisition as the correlation between Q22 on organizational learning and the Technology socio-technical construct was insignificant. As well, a poor correlation exists in the second survey results between the Infrastructure socio-technical

construct of resource allocation to improve production practices and the Technology sociotechnical construct of technology adoption.

Approximately 68% of manufacturers responded affirmatively to Q9 of the second survey, which asks, "How likely is your organization to promote the productivity and innovation of teams while minimizing conflicts?" There were 55 manufacturers identified holding patents or approximately 37% of the sample population. As well, a significant correlation was found between Q22 on organizational learning and Q9. Additionally, a significant presence of the keyword 'Design' was found among the manufacturers studied. The innovation study appears to support the second survey responses (Roth et al., 2024).

5.6. Limitations of the Study

The research conducted in this web scraping project is focused solely on the socioeconomic context of regional manufacturers in western Minnesota and eastern North Dakota. The industry sector in this geographic area is smaller in scope and may not represent the depth of capabilities performed by the manufacturing sector in larger geographic areas. Additionally, web scraping was conducted during the timeframe of a thirty-day window of time in November of 2023, which is a static period. Continuous data collection was not conducted to evaluate trends during a longer period.

5.7. Contribution of Web Scraping Research

The web scraping research project contributed a regionally focused mapping of the current investment decisions of regional manufacturers in selected Industry 4.0 technologies. As well, the level of patent holders may indicate future technological needs, which may be assessed through similar web scraping projects conducted over a longer period.

5.8. Recommendations for Future Study

This study is an innovative method of collecting relevant information on the use of emerging communication and information technologies employed by the regional manufacturing sector. Conducting subsequent web scraping research periodically will reveal the dynamic trends in the integration of Industry 4.0 technologies. Conducting a similar study over time in the manufacturing sector in newer geographic markets will establish a comparative trends analysis study. Future research could include central and western North Dakota, as well as, central and eastern Minnesota geographic regions. Added manufacturing information, such as NAICS codes, could be included in the analysis. Future analyses may combine data from patents, websites, news activities, as examples, to produce a holistic review of the Industry 4.0 landscape and innovation activities in Minnesota and North Dakota (Russo et al., 2022) (Crijns et al., 2023).

5.9. Conclusion

Continuous assessment measures and outreach to promote innovation are signs of science, technology, and innovation policy (Kinne & Lenz, 2021). Digital transformation promotes innovation, market competitiveness, and sustainability for regional manufacturers. Studies have shown that industries depicted by high energy consumption, yet low technological input, may observe through the implementation of artificial intelligence technologies, reduced carbon emissions through energy efficiency, increased financial performance, and developing green innovation (Gao, 2023). Surveys are commonly used as assessment tools among diverse industry sectors. The survey tools provide a wealth of information on the current state of practice in a specific industry. Web scraping is an inexpensive tool to support anonymous survey methods, test hypotheses, or extend existing findings (Speckmann, 2021). The results of this study demonstrate the utility of web scraping to identify current technological aptitudes and competitive advantages

within the manufacturing sector. Web scraping combined with the two survey tools used provide significant insights into the industrial sectors current organizational design status in the Industry 4.0 context.

6. DISCUSSION

When combined, the first and second surveys act as a holistic sequential socio-technical management competence tool to advance the work organization. As suggested in *2.1.9 Implementing Industry 4.0 by utilizing a Socio-Technical SWOT analysis,* the Socio-technical surveys may be integrated into a strengths, weaknesses, opportunities, and threats (SWOT) analysis prior to the completion of the business model canvas to jointly optimize the social and technical factors of an organization within the context of the organization's specific tasks and goals during the Industry 4.0 implementation process. As well, the socio-technical surveys are issued throughout the Technology, Resilience, and Innovation phases of the digital transformation process to provide additional statistical analyses. This method is a new business application for the Socio-technical theory that serves to successfully achieve both Industry 4.0 and Industry 5.0 transformations.

The first survey addresses the digital transformation of Industry 4.0, which impacts both social and technical aspects of work organizations and is increasing the interfaces between human labor and computer-controlled processes. The replacement of low-skilled work tasks by highly skilled, non-routine work is creating a more human work design. Digitalization is influencing organizational learning by creating competencies for the use of innovative Industry 4.0 technologies (Kuper, 2020). Digitalization is also providing an expansion of opportunities in streamlining, redesigning, and redeveloping organizational processes and procedures – the technical components of a socio-technical work organization (Kurtz et al., 2023).

The socio-technical constructs used in this survey were based on a socio-technical framework of identifying cross-system relationships between social and technical system

components, such as people and processes, to develop system-level advice and to lead organizational change (Davis et al., 2019).

In reference to Table 4, SMEs and large manufacturers surveyed in Minnesota and North Dakota need to invest more time in the socio-technical tasks involved with testing results with stakeholders and utilizing data to make meaningful contributions to increase productivity. The Testing the Results with Stakeholders construct requires resources and a long-term strategy. Resources may include tools, materials, final products, equipment, and human resources. Both the physical assets and the personnel hold tangible information that may be shared and processed (Li et al., 2019). As the socio-technical construct questions suggest, this process requires an investment in organizational learning for employees, resources for employees at all levels, inclusion of external stakeholders in the data-capturing process for decision-making at the organization design level, and surveying of all internal and external stakeholders to inform sociotechnical organizational design. Iterating and amending the organizational design process requires a multidisciplinary task to continuously evaluate, extract, and use data meaningfully. The sociotechnical principle of incompletion supports this focus of identifying the solutions that must first be implemented. The socio-technical design process is continuous improvement and must constantly be monitored.

The first survey results illustrated that, among all Minnesota and North Dakota manufacturers, a strong, positive correlation between the socio-technical constructs and Industry 4.0 integration exists, yet increased productivity is not pervasive. Additionally, there may be a lack of diffusion of knowledge regarding the utility of innovative technologies, hindering work teams from practicing responsible autonomy. This finding may indicate gaps in organizational learning, leading to a deficit in the technical knowledge of leadership and employees among

SMEs and large manufacturers in the region to extract data from newer autonomous and communication technologies. Moreover, this outcome may indicate that the organizations employing these technological innovations are operating on short-term strategic plans, rather than long-term strategies. This finding answers the first research question of how applicable sociotechnical design principles are to the Industry 4.0 context among North Dakota and Minnesota manufacturers.

The second research question focused on whether a positive correlation between Industry 4.0 and increased productivity among manufacturers in North Dakota and Minnesota would be observed. A negative correlation between Industry 4.0 integration and productivity among all manufacturers surveyed was identified. The root cause of this outcome may be related to inequalities in how the socio-technical design constructs are applied with each work organization. Additionally, the output of data from the innovative technologies may also be under-utilized or not leveraged toward furthering organizational design. As well, there may not be a significant level of Industry 4.0 technology adopted to measure this significance.

There is an aggregately negative correlation between socio-technical constructs and increased productivity regardless of small, medium, or large business size in Minnesota and North Dakota. This outcome is also reflected in a poor correlation between Industry 4.0 and increased productivity. Although the organizations surveyed are utilizing socio-technical design methods, the social and technical aspects are not jointly optimized for extracting maximum value from Industry 4.0. There are inequalities among how the socio-technical constructs are being leveraged, which is contrary to the socio-technical design principle of incompletion, which ensures continuous improvement. This design principle is integral to effectively implementing both Industry 4.0 and socio-technical theory frameworks in organizational design. This outcome

addresses the third research question to whether a positive correlation between socio-technical design principles and increased productivity would be observed.

However, assessing only the small manufacturers in Minnesota and North Dakota, a weak, positive relationship between Industry 4.0 integration and increased productivity was observed. This feedback supports the second research question. Possible explanations for this outcome are being unaware of how to capture data fully and not having the technically trained staff to assist with the Industry 4.0 implementation process. The small manufacturers indicated a strong, positive correlation between socio-technical constructs and Industry 4.0 integration, which may indicate a trajectory toward, but not complete realization of, joint optimization of both social and technical factors. This finding may indicate a prematurity of implementing Industry 4.0 prior to socio-technical design readiness. This insight supports the first research question. The full sociotechnical framework is applied to support organizational design efforts in small manufacturers surveyed from Minnesota and North Dakota. However, the organizational design may not employ socio-technical theory design continuously; therefore, the outcome of minimal productivity.

Medium-sized manufacturers in Minnesota and North Dakota are not gleaning value from Industry 4.0 to increase productivity. The socio-technical design is directly related to Industry 4.0 integration, as it reflects the organization's preparedness to adopt new operational strategies. The socio-technical design is partially implemented, providing an environment for new technology adoption. A poor correlation between socio-technical constructs and productivity reveals that possible knowledge barriers exist to the operational practices of the manufacturer to extract value from the organizational design and new technologies, thus meaning that the full socio-technical framework is not jointly optimized.
Large manufacturers in Minnesota and North Dakota experienced a negative correlation between Industry 4.0 (Q12) integration and increased productivity (Q21), which may indicate the lack of leadership's technical knowledge about how to extract and use data from new technologies. A positive correlation existed between all socio-technical constructs and Industry 4.0 integration, which may indicate that this framework is conducive to new and increased technology adoption rates.

Considering specifically Minnesota manufacturers, a negative correlation between Industry 4.0 and increased productivity was observed, which may indicate a lack of technical expertise to capture value from new technologies. A negative correlation between socio-technical constructs and increased productivity existed, indicating that the framework is not fully employed to capture operational efficiencies.

The North Dakota manufacturers surveyed displayed a strong, positive correlation between socio-technical constructs and Industry 4.0 integration, indicating that socio-technical design facilitates the adoption of newer technologies. A positive correlation existed among all socio-technical constructs, indicating that manufacturers are actively engaged in socio-technical design frameworks. The weak correlation between Industry 4.0 integration and increased productivity indicated a potential lack of technical knowledge to address the full adoption of new technology to realize all of its benefits. Additionally, it indicates that the continuous nature of socio-technical design is not utilized at its full capacity.

Industry 4.0 allows for product-centric organizations to move toward servitization, creating a closer relationship with the consumer market (Sony, 2020). Servitization is defined as providing added service value to products, whether service-derived value co-creation or enhanced service-derived value co-creation, to foster organizational sustainability. The five types of

manufacturing servitization value co-creation models are product extension, product enhancement, leading product, business unit, and core capability. The value co-creation is observed with enterprises and upstream suppliers, between enterprises and consumers, and among the participation of stakeholders (Li et al., 2022).

A greater volume of data and analytics resulting from the implementation of Industry 4.0 will create bargaining power for buyers. The contribution of analytics for implementing smart services will be prescriptive – what to do?, predictive – what will happen?, diagnostic – why will it happen?, and descriptive – what will happen? (Neuhuttler et al., 2023). There are pros to implementing Industry 4.0, which include competitive advantage, operational efficiency, improved ergonomics, and long-term sustainability. The cons include the negative impact of financial investment in all operationally necessary Industry 4.0 technologies, lack of data confidentiality, and the necessary technical skillsets among leadership and employees of the socio-technical organization (Sony, 2020). The last previous disadvantage noted interferes with the sharing of innovation throughout an organization (Tortella et al., 2022). Industry 4.0 implementation must be welcomed by an organization that has jointly optimized its social and technical aspects to receive the full benefits of productivity from these innovations. Successful implementations provide employees with greater control and freedom and align closely with ownership and empowerment (Minshull et al., 2022).

The second survey was also influenced from the socio-technical framework developed by Davis et al. Their proposed socio-technical framework assesses the six interrelated components of goals, people, building/infrastructure, technology, culture, processes/procedures within the external environment of financial/economic, stakeholders, and regulation. This socio-technical framework supports both predictive and design work. The framework was explained as major

steps involved in analyzing and understanding an existing socio-technical system (Davis et al., 2014) This study is a unique approach to analyzing the organizational joint consideration of Industry 4.0, socio-technical factors, and predictive work, as the socio-technical assessment steps were transformed into questions and posed to employees of small, medium, and large manufacturing firms. These survey questions provide a useful tool for socio-technical competence management within an organization when jointly considering human factors while implementing new technologies. Alternately, these socio-technical survey questions may also be utilized in a Socio-technical SWOT analysis of each of the nine components of a business model canvas. Additionally, the survey may serve the purpose of checking the sustainability status of small, medium, and large manufacturing firms by operators from upper management to ensure that new investments in Industry 4.0 technologies and generated data usage therefrom are leveraged adequately to support productivity targets. Small and medium-sized manufacturing firms may be unfamiliar with utilizing this type of analysis to improve an organization. This socio-technical survey tool illustrates an emerging management approach with SMEs in supporting continuous improvement efforts.

In the second survey, in reference to the simple frequency chart outcomes described in the results section the following assumptions are made of the total surveyed population. Aggregately very few manufacturers are utilizing decision support or judgment substitution through learning algorithms from various applications. Two out of 35 manufacturers surveyed that utilize information technology solutions in the workplace were likely to establish a reduced daily work schedule. Nearly 94% of manufacturers responded affirmatively to continuously improving communication across departments and teams to instill employee engagement. However, less than half of manufacturers surveyed are leveraging a socio-technical organizational design framework

to guide the flow of information and communication, which is described as data gathering, analysis and interpretation, summarizing the findings, testing the results with stakeholders, and iterating and amending as necessary to communicate recommendations to employees and stakeholders. Socio-technical design is critical to predictive work, such as productivity planning and labor scheduling. These communication strategies are essential to successful Industry 4.0 implementation.

Techniques that contribute to understanding the interrelatedness of social and technical factors of the organization, such as with the development of cross-functional diagrams, are being evaluated by 40% of the businesses. The promotion of productivity and innovation is reported to occur in 68.57% of respondents across business sizes. The innovation process is often observed as the four stages of research, design, prototyping, and testing (Peruzzini et al., 2023). Management innovation is defined as 'the generation and implementation of a management practice, process, structure, or technique that is new to the state of the art and is intended to further organizational goals', which is affiliated with social changes within the work organization. The traits of this type of practice are that it is diffused, continuous, and incremental and that it relies on the interrelationships of diverse stakeholders to assimilate and apply technical knowledge. The application of the socio-technical survey questions in conjunction with the SWOT analysis of the business model canvas will support achieving innovation goals.

A large-scale study of Dutch firms reported that management innovation is a profitable performance strategy as it supports the use of technological innovations to make better market decisions. Ultimately, successful firms are employing joint optimization of social and technical factors to manage innovation processes (Cerne et al., 2023). Manufacturing firms continuously support innovation initiatives, which are found in inter-departmental and independent forms.

Examples are business innovation labs, hackathons and start-up events in coordination with suppliers, customers and employees to develop innovation aptitudes (Kurtz et al., 2023). From the work task perspective, examples from corporations, such as Google illustrate a 20% policy, where employees engage in personal projects that are innovative in nature during one-fifth of their work hours. Results of this flexible working arrangement have been products, such as Gmail, Google News, and Adsense (Kostadinova & Vladkova, 2022). As well 3M encourages a 15% culture where employees are encouraged to establish time to pursue innovative ideas. The experimentation may include new technology, process improvement, and team forming to support emerging trends. Innovations such as the Multilayer Optical Film, Cubitron, Abrasive Grains, Emphaze, AEX Hybrid Purifier, APC Flash-Free Adhesive, and Post-It Notes have been created in this manner [\(https://www.3m.co.uk/3M/en_GB/careers/culture/15-percent-culture,](https://www.3m.co.uk/3M/en_GB/careers/culture/15-percent-culture) Accessed 3 October 23).

Sixty percent of manufacturers are leveraging a bottom-up problem-solving approach, yet slightly over 62 percent of employers rather than employees are leading the effort of specifying roles, responsibilities, and/or tasks that are specific to a job when optimizing or streamlining a process. In response to supporting the allocation of resources and work to change and improve production practices, organize work tasks, and strengthen internal cooperation, only 68.57% responded in the affirmative, which indicates that there will be significant gaps in the needed resources for continuous growth and will be observed in specific correlations addressed in this section. The reduced work hour goal (Q13) did not have a significant relationship with bottom-up problem-solving approach of (Q18). Yet, the reduced work hour goal (Q13) had a significant relationship with responsible autonomy (Q21). Also, responsible autonomy (Q21) had a strong relationship with the bottom-up problem-solving approach (Q18). In summation, Q18 is important to Q21 and Q21 is important to Q13. The lack of a bottom-up problem-solving approach appears to be a required factor needed for attaining a reduced work hour goal. The socio-technical SWOT analysis prior to the completion of the business model canvas is a framework designed to facilitate the engagement of all employees in the strategic planning process or a bottom-up problem-solving approach that has been emphasized by academic researchers as a critical factor to reducing work hour schedules with manufacturers.

In reference to Table 16, small manufacturers surveyed in Minnesota and North Dakota reported that with regards to Q22 on organizational learning, significant gaps in technical knowledge acquisition exist as the correlations between this question and the technology sociotechnical construct were insignificant. The Q13 reduced daily work hour goal corresponded significantly only to the technology construct. Therefore, a socio-technical imbalance is present, which may cause the lack of opportunity in attaining reduced work hour goals.Also, with alpha at .05, Q21 on responsible autonomy and Q9 on the promotion of productivity and innovation did not significantly correlate. As well, Q22 on Organizational Learning and Q21 on Responsible Autonomy did not significantly correlate.

In reference to Table 17, medium-sized manufacturers surveyed in Minnesota and North Dakota reported that there is no significant correlation between organizational learning and a reduced daily work hour goal among medium-sized manufacturers in North Dakota and Minnesota. A significant correlation was not identified between Q21 on responsible autonomy and Q9 on the promotion of productivity and innovation. As well, a significant correlation was not identified between Q22 on organizational learning and Q21 on responsible autonomy.

In reference to Table 18, large-sized manufacturers surveyed in Minnesota and North Dakota reported there is no correlation between Q22 on organizational learning and Q13 on

establishing a reduced daily work hour goal to serve to jointly optimize the technical and human factors of an organization to achieve higher productivity and employee wellbeing. A significant correlation was not identified between Q22 organizational learning and Q21 responsible autonomy. As well, a significant correlation was not identified between Q21 responsible autonomy and Q9 the promotion of productivity and innovation.

The first research question sought to identify a relationship between the implementation of organizational practices that support organizational learning and training and reduction of time on tasks/productivity. These outcomes answer the first research question that organizational learning will not be significantly correlated with a reduced daily work hour goal among manufacturers in Minnesota and North Dakota. In reference to Figure 15, the correlation between responsible autonomy (Q21) and a culture of organizational learning (Q22) was not observed as significantly positive. However, the cross comparison of productive organizational learning (Q11) and responsible autonomy (Q21) illustrated that 61% of responses were affirmative to focusing on organizational learning as well as engaging in responsible autonomy with employees to achieve specific goals. The difference between Q22 and Q11 is that Q22 suggests full implementation of organizational learning within the culture where the process is observed as continuous.

They also answer the second research question focused on whether a positive correlation between responsible autonomy and the promotion of productivity and innovation would be observed. Responsible autonomy did not show a strong positive correlation with the promotion of productivity and innovation (Q9) with manufacturers surveyed.

The third research question focused on whether a positive correlation between responsible autonomy and organizational learning among regional manufacturers would be observed. There is no significant correlation between responsible autonomy and organizational learning among

small, medium, and large regional manufacturers observed. These outcomes answer the third research question that responsible autonomy will not significantly correlate to a culture of organizational learning among regional manufacturers.

The survey was based on the socio-technical framework developed by Davis et al. This socio-technical framework identifies the social factors of an organization as people, goals, and culture and the technical factors of infrastructure, technology and processes as interdependent. These elements operate within an external environment that offers unique economic conditions, diverse stakeholders, and regulation. The theoretical insights of various academic researchers cited previously contributed to the alignment of a new assessment. This study is a unique approach to analyzing the socio-technical design maturity of manufacturers in Minnesota and North Dakota when considering the implementation of reduced daily work hour goals. Critical success factors pertaining to leadership, responsible autonomy, organizational learning, and communication have been recommended by academic researchers and practitioners when leading organizations towards a modern work environment. The results of the second survey validate the results of the first survey by the authors.

The first survey and academic research journal article provide a useful tool for assessing socio-technical competence management within an organization when jointly optimizing social and technical factors of an organization (Roth & Farahmand, 2023). The second survey tool in combination with the first survey tool are significant instruments for conducting this research and may serve the purpose of checking the socio-technical sustainability status of small, medium, and large manufacturers in the context of a SWOT analysis prior to developing a business model canvas. Organizations continue to digitally transform to offer flexible work arrangements for

employees. This survey illustrates an emerging management approach with SMEs in supporting continuous improvement efforts (Roth & Farahmand, 2023).

The IoT and Cloud Computing are the least expensive and easiest technologies for SMEs to adopt. However, there is a low investment indicated in the web scraping results in both technology categories. Socio-technical systems theory has been noted as increasing the adoption rates of technology (Macron et al, 2021). This outcome corresponds to the first research question. A significant correlation was found between socio-technical systems design and Industry 4.0, however, a gap exists in the upward increase potential for investments that could be made in newer information and communication technologies. The web scraping results also appear to support the results for the second research question on the lack of correlation between Industry 4.0 and Increased Productivity among manufacturers in the region. There is minimal diversity of Industry 4.0 technologies used, which may indicate a lesser investment throughout a production process of Industry 4.0. Therefore, increased productivity would not be as readily observed. The significance level of representation of the keywords 'Data' and 'Big Data' from the web scraping project appears to illustrate a presence of a socio-technical systems design work of the Data Gathering socio-technical construct studied in the first survey. The results did not support the third research question, where a significant relationship was not found between socio-technical systems design and increased productivity.

The fourth through sixth research questions supported activity of the second survey. The fourth research question focused on identifying a significant correlation between organizational learning and reduced daily work hour goals, which was not supported by the survey results. The web scraping results illustrated a minimal diversity of Industry 4.0 investments, which may indicate that a culture of organizational learning is not pervasive and significantly correlated to

attain a reduced daily work hour goal through the aid of newer technologies. Also, no significant relationship was found in the fifth research question focusing on responsible autonomy to the promotion of productivity and innovation. Only 37% of manufacturers in the regional sample were identified as patent holders. The low percentage would indicate an insignificant promotion of productivity and innovation, which does not allow for the opportunity for this activity to be influenced. Lastly, the sixth research question focuses on the correlation between responsible autonomy and organizational learning. There was no significant relationship found. The goals of Industry 4.0 is to gain autonomy, decentralization, responsibility, and teamwork (Tortorella et al., 2022). This supports responsible autonomy as employees have greater opportunities to customize technology. The presence of learning algorithms is one example of providing opportunities for responsible autonomy to thrive as employees focus on the social subsystems of people, culture, and goals (Fischer et al., 2023). The lack of a presence of diversified information and communication technologies may indicate a lack of an environment to foster responsible autonomy, therefore a lack of correlation may exist supporting the survey outcomes for the sixth research question.

7. CONCLUSION

Researchers are focusing on identifying further insights as to how Industry 4.0 relates to value chains and supply networks, clusters and industrial districts, readiness and adaptation of regional industries, innovation development and ecosystems, and labor markets (Fraske, 2022). The North Dakota and Minnesota manufacturers surveyed illustrate the changing manufacturing environment that is shifting toward the adoption of the new technologies of Industry 4.0 and the sustainability characteristic of Industry 5.0. Increasing the investments in both social and technical factors will provide operational benefits (Minshull et al., 2022).

Practices that facilitate the implementation of Industry 4.0 have been noted as understanding the benefits of practices, adoption research and development, management support, training and development programs, and resources (Trehan & Machhan, 2022). Organizations undertaking the socio-technical joint optimization process of their organizations with both survey tools will incrementally work towards freeing up resources to increase productivity. Starting with smaller projects that can be measured with knowledge performance indicators, such as the sociotechnical constructs, lead-time reduction, number of projects delivered per period and cost savings, will prepare for the implementation of large-scale projects (Roy et al., 2023).

The limitations of the first survey study include the small sample size of regional manufacturers that was assessed. Additionally, companies may not be utilizing Industry 4.0 and therefore are not benefiting from its advantages. More education and training for managers and employees on the benefits of socio-technical awareness as both an antecedent to Industry 4.0 adoption and an established practice in the context of Industry 4.0 are needed to develop a future cohort of enhanced manufacturers in the region. Additional studies should be conducted to determine the socio-technical readiness of manufacturers in the region, as doing so would lead to

an Industry 4.0 integration readiness. Moreover, future studies should be conducted to assess how manufacturers in North Dakota and Minnesota are utilizing Industry 4.0 technologies to determine opportunities for and challenges to realizing increased productivity levels from these sociotechnical organizations and to inform various industrial sustainability policies for regional economic development authorities. As well, an exploration into the development of a regional Industry 4.0 competence center that aims to create synergies and serve as a catalyst for inclusivity in innovation and development among diverse stakeholders of the economic ecosystem, providing access to insights, and mitigating the pressures of rapidly adopting newer technologies on small and medium-sized businesses should be considered (Prodi et al., 2022).

Academic researchers agree that studies be guided by the mission to eliminate the obstacles for small and medium-sized businesses to access Industry 4.0 technologies, which provide significant strategic competitive advantages for firms both regionally and internationally (Fernandes et al., 2022). Strategic planning is critical to the success of digital transformation. Led by employees, barriers, challenges, and opportunities to providing employees with reduced daily work hours will be identified and solved in a bottom-up leadership methodology. Employee autonomy is intrinsic to the successful implementation of job crafting in the Industry 4.0 context, as it contributes to a productive organizational culture of learning and productive behavior (Whiteoak, 2022). Organizational culture is illustrated through a willingness to change, social collaboration and is supported through information and knowledge sharing (Li et al., 2019) Job demands require that the needed resources are allocated for workers to reduce the incidence of burnout (van Kleeff et al., 2023). A method of avoiding conflicts and failed projects is through engagement with those employees completing the tasks involved with high levels of productivity

and innovation. Trust is a key factor in the relationship between employees and managers to support these endeavors (Enehaug, 2017).

Leadership vision must be informed by the possible growth opportunities with the adoption of the new communication and information technologies of Industry 4.0 (McDermott et al., 2023). Digital leadership encourages new methods of organizing and communicating. This leadership trait supports employee autonomy, innovation, and creativity through supporting employee job crafting, which is an employee-led job design strategy. Key digital leadership skills are a bottom-up organizational change strategy, a future-oriented vision, digital literacy, and adaptability (Zhu et al., 2022). A key example of organizational change driven by digital leadership is through the development of cross-functional teams, which aids with the dispersion of communication throughout an organization (Leso et al., 2022).

The six socio-technical constructs of this study described how the current organizational design practices contribute to supporting organizational learning, responsible autonomy, and promoting productivity and innovation to achieve reduced daily work hour goals among small, medium, and large manufacturers. This dissertation provides theoretical contributions and is a timely review of the socio-technical design implementation in the region within the manufacturing sector. The study advances the socio-technical practice by highlighting critical socio-technical factors contributing to successful digital transformation strategy. Jointly optimizing both technical and social organizational factors will improve overall performance.

The limitations of the second survey study include the small sample size of regional manufacturers that was assessed. Additionally, companies may not be utilizing Industry 4.0 and therefore are not benefiting from its advantages. As well, few companies are embracing reduced work week schedules or flexible work arrangements in the manufacturing industry in Minnesota

and North Dakota. A reason for the regional inattention to this long-term sustainability goal may be a perceived lack of benefit for its intended workforce and to the organization. More education and training for managers and employees on the benefits of socio-technical design in the context of Industry 4.0 are needed to develop a future cohort of enhanced manufacturers in the region.

Future studies should be conducted to assess Industry 4.0 technologies and its implementation and to understand the current level of implementation and commitment among manufacturers in Minnesota and North Dakota to determine the opportunities for and challenges to realizing reduced daily work hour schedules. Future research can build on this study by enriching the survey tools or utilizing the socio-technical SWOT analysis prior to developing a business model canvas as part of longitudinal studies of strategic planning among small, medium, and large manufacturers in the region at various levels of Industry 4.0 investment. As well, future research of how socio-technical design in the Industry 4.0 context supports value co-creation processes should be examined.

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APPENDIX A. DATA FROM FIRST SURVEY

Table A1. Data from First Survey

Table A1. Data from First Survey (continued)

APPENDIX B. DATA FROM SECOND SURVEY

Table B1. Data from Second Survey

APPENDIX C. DATA FROM WEB SCRAPING PROJECT

Table C1. Data from Web Scraping Project

APPENDIX D. SURVEY RESULTS OF ARCHITECTURE, ENGINEERING, AND

CONSTRUCTION INDUSTRIES

Table D1. First Survey for Architecture, Engineering, and Construction industries – All Business Sizes - Pearson Correlation Coefficient

Table D2. First Survey - Polychoric Coefficient of Industry 4.0 Integration (Q12) Relationship with Increased Productivity (Q21)

Table D3. First Survey - Architecture, Engineering, and Construction by Business Size

Table D4. First Survey – Polychoric Coefficient for Architecture, Engineering and Construction Industries for Q3 and Q12 Relationship

Table D5. Relationship of Q3 and Q21 for the Architecture, Engineering, and Construction Industries

Table D6. Polychoric Coefficient for the relationship of Q3 and Q21 for Architecture, Engineering, and Construction Industries

Table D7. Second Survey - Architecture, Engineering, and Construction

Table D8. Pearson and Polychoric Coefficients for Second Survey – Architecture, Engineering, and Construction

Table D9. Second Survey – Architecture, Engineering, and Construction

Statistic	Value	ASE
Gamma	0.7895	0.2411
Kendall's Tau-b	0.4599	0.1935
Stuart's Tau-c	0.4959	0.2433
Somers' D C R	0.5357	0.2464
Somers' D R C	0.3947	0.1629
Pearson Correlation	0.5155	0.1945
Spearman Correlation	0.4914	0.2120
Polychoric Correlation	0.7163	0.2538
Lambda Asymmetric C R	0.0000	0.0000
Lambda Asymmetric R C	0.2500	0.2165
Lambda Symmetric	0.1111	0.0940
Uncertainty Coefficient C R	0.1560	0.0701
Uncertainty Coefficient R C	0.2781	0.1506
Uncertainty Coefficient Symmetric	0.1999	0.0951

Table D10. Second Survey – Architecture, Engineering, and Construction Q14 by Q21

Table D11. Second Survey – Architecture, Engineering, and Construction – The Relationship of Q14 by Q24

Table D12. Pearson and Polychoric Coefficients for Second Survey – The Relationship of Q14 and Q24 - Architecture, Engineering, and Construction

APPENDIX E. SURVEY RESULTS OF BUSINESS, FINANCIAL, SALES, AND

LOGISTICS INDUSTRIES

Table E1. First Survey – The Relationship between Digital Technology Integration (Q3) and Industry 4.0 Integration (Q12) - Business, Financial, Sales, Logistics

Table E2. First Survey – The Relationship between Digital Technology Integration (Q3) and Industry 4.0 Integration (Q12) - Business, Financial, Sales, Logistics

Table E3. First Survey - The Relationship between Industry 4.0 Integration (Q12) and Increased Productivity (Q21) - Business, Financial, Sales, Logistics

Table E4. Second Survey – The Relationship between Q14n and Q5 – Business, Financial, Sales, Logistics

Table E5. Second Survey – The Relationship between Q15n and Q5 – Business, Financial, Sales, Logistics

Table E6. Second Survey – The Pearson and Polychoric Coefficients for the Relationship between Q15n and Q5 – Business, Financial, Sales, Logistics

APPENDIX F. SURVEY RESULTS OF COMPUTER AND INFORMATION

TECHNOLOGY INDUSTRY

Table F1. First Survey – The Relationship between Digital Technology Integration (Q3) and Industry 4.0 Integration $(Q12)$ – Computer and Information Technology

Table F2. First Survey – Pearson and Polychoric Coefficients for Digital Technology Integration (Q3) and Industry 4.0 (Q12) – Computer and Information Technology

Table F3. First Survey – The Relationship of Industry 4.0 Integration (Q12) and Increased Productivity (Q21) - Computer and Information Technology

Table F4. First Survey – Pearson and Polychoric Coefficients of the Relationship of Industry 4.0 Integration (Q12) and Increased Productivity (Q21) – Computer and Information Technology Industry

Table F5. First Survey – Relationship of Gathering Data (Q3) and Increased Productivity (Q21) – Computer and Information Technology Industry

Table F6. First Survey – Pearson and Polychoric Coefficient for the Relationship of Q3 and Q21 – Computer and Information Technology Industry

Table F7. Second Survey – Relationship of Q14n and Q5 - Computer and Information Technology

Table F8. Second Survey – Pearson and Polychoric Coefficients - Computer and Information Technology

Table F9. Second Survey – The Relationship between Q15 and Q5 - Computer and Information Technology

Table F10. Second Survey – The Relationship between Q15 and Q5 - Computer and Information Technology

Table F11. Second Survey – The Relationship between Q15 and Q13 - Computer and Information Technology

Table F12. Second Survey - Pearson and Polychoric Coefficients - Computer and Information Technology

Statistic	Value	ASE
Gamma	1.0000	0.0000
Kendall's Tau-b	0.6804	0.1266
Stuart's Tau-c	0.8000	0.2263
Somers' D C R	0.8333	0.1800
Somers' D R C	0.5556	0.1247
Pearson Correlation	0.7222	0.1861
Spearman Correlation	0.7404	0.1477
Polychoric Correlation	0.9974	0.0000
Lambda Asymmetric C R	0.0000	0.4714
Lambda Asymmetric R C	0.5000	0.6124
Lambda Symmetric	0.2000	0.4767
Uncertainty Coefficient C R	0.2971	0.0953
Uncertainty Coefficient R C	0.5880	0.2231
Uncertainty Coefficient Symmetric	0.3947	0.1302