Flinders University

Digital Transformation for Production Performance

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ABSTRACT

Industry 4.0, the digital transformation of industrial production, seeks to address production's performance challenges. It aims to optimize industrial production through technological and organizational changes that integrate the value chain end-to-end, inducing smartness along the chain. The internationalization of the production value chain through globalization increased the technological, socio-economic, and legal requirements of operating the enterprises that form the chain. It increased the variability in the economic environment of production and complicated the social license requirements. The pace of technological change, growing sustainable business advocacy, and requirements for product customization also created challenges that further increase the complexity of industrial production. Furthermore, the COVID-19 pandemic underscored the importance of flexibility of production infrastructure during crises.

Existing literature remains limited in capturing the complexity of the industrial digital transformation process and its value proposition. To advance the practice of industrial digital transformation, this study addresses the overarching research question 'what is the value proposition of Industry 4.0, and how is it delivered'? The question is addressed by modelling the industrial digital transformation process and determining the contribution of digital transformation maturity to production performance. In addressing this issue, this study uses a mixed-method approach. It first uses qualitative research to develop a model for the Industry 4.0 process and its value proposition in organizations - how Industry 4.0 integrates digital technology into the production process, develops smart enterprise organizational capabilities, and delivers performance benefits. It then robustly tests this model with production managers using quantitative research. The results guide managers in creating digital transformation strategies for their organizations.

The study makes theoretical contributions to the digital transformation literature by providing a model for driving digital transformation maturity in production organizations and establishing its performance impacts across the value chain. The study integrates and extends the systems, maturity modelling, and dynamic capability theories. This study's outcomes are important in assisting organizations in assessing their level of digital transformation maturity to progress their Industry 4.0 journey.

The study finds that technology use builds smartness across the value chain – factory, supply chain, and products. Furthermore, the study provides insights into the value delivery potential of different value chain segments. It established that digital transformation investment in the factory has higher value potential than the supply chain and products. It provides a deeper context to investments in industrial digital transformation and guides management strategy.

The study also provides practical implications for managers. It establishes that Industry 4.0 fosters the smartness of organizations. Smartness equips the enterprise with the flexibility to respond robustly to challenges of economic variability, customization, and increasing cost of the social license of doing business. The nuances of smartness across the value chain give managers levers to craft strategies targeting their specific organizational priorities, including productivity, sustainability, customer experience, and worker safety.

DECLARATION

I certify that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

Signed...

Date.....30th May 2023............................

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I want to start by thanking God for my life and the grace I have enjoyed in conceiving and completing this work.

My gratitude to my wife, Jola-Ade, and our son, Irewole, for their sacrifice and generosity throughout this process is impossible to quantify. If it were possible, their names should appear on the certificate. Their encouragement meant everything to me during this endeavour.

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I appreciate my parents and siblings for their help and support throughout this process, my family has been an unbelievable pillar, and I am blessed to belong.

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I dedicate this thesis to the memory of my late father, Olayinka Tony Abiodun, C.Eng., who passed on as I was finishing. I would not have done this without him. RIP.

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1 INTRODUCTION

1.1 Overview

From pandemic to war, surviving crises demands flexibility in production infrastructure (Ho et al., 2022; Okorie et al., 2020). A commonality between the second world war (WWII) and the COVID-19 pandemic is the government's use of emergency powers to mandate repurposing production resources (Bender, 2020; Donnelly, 2020; Vergun, 2020). However, while some manufacturers achieved actual repurposing of plants in relatively quick periods in the COVID-19 scenario, new plants generally had to be built during WWII. Focusing on the automotive industry, which was heavily impacted in both scenarios, automotive manufacturers repurposed plants, sometimes in days, to produce ventilators and other essential healthcare products such as masks and hand sanitizer, which had become critical for public health (Liu et al., 2021). However, during WWII, the Chrysler-owned Dodge had to build the Dodge Chicago Aircraft Engine Plant, which built engines for B29 Bomber aircraft between 1942 and 1944 (Bailey, 1945). Similarly, Ford’s Willow Run, also known as Air Force Plant 31, its manufacturing facility for the B24 Liberator aircraft, was built between 1940 and 1942 (Duford, 1997).

The capacity to repurpose production facilities requires a high degree of flexibility (Ho et al., 2022; Okorie et al., 2020). Industry 4.0, the digital transformation of industrial production, has been recognized as a significant factor in successfully repurposing production infrastructure during the COVID-19 pandemic (Malik et al., 2020; Okorie et al., 2020). Industry 4.0 enhanced the flexibility of production systems through smart functionalities like additive manufacturing (Kumar, 2018) and self-organization (Qin & Lu, 2021). This flexibility is essential for the current and future socio-economic, environmental and political challenges posed to industrial production performance.

Industry 4.0 is the digital transformation that spans the entire production value chain (Bartodziej, 2017). In the evolution towards Industry 4.0, front-end business aspects of the production value chain used information technology (IT), resulting in the application of enterprise information systems like Enterprise Resource Planning (ERP) systems in industrial production (Mo, 2009; Upton & McAfee, 2000). Industry 4.0 extended this by employing advanced technologies to digitalize the operating technologies (OT) (or machine parts), facilitating the integration of the physical and virtual elements of the production enterprise (Ghobakhloo & Iranmanesh, 2021). It results in smart, high-performing production value chains (Lichtblau et al., 2015; Schuh et al., 2017). Industry 4.0 underpins the fourth industrial revolution (Schwab, 2017), based on cyber-physical integration (integrating physical and virtual elements of production) to create production enterprises that are digitally integrated end-to-end (BMBF, 2014; Lichtblau et al., 2015). Developing Industry 4.0 capabilities is complex (Szalavetz, 2019); it is characterized by interactions among diverse technological, operational, and functional factors, requiring significant technology-driven organizational change. Justifying the endeavor is also nontrivial due to the difficulty in evaluating the return on investment (Almeida et al., 2022). This thesis seeks to contribute to addressing strategic planning challenges for Industry 4.0 in industrial organizations by establishing its value proposition by determining the impact of Industry 4.0 maturity on organizational performance.

The resultant production system of Industry 4.0 is socio-technical, comprising technical and non-technical entities, including people, materials, resources, technologies, processes, and organizations (Lichtblau et al., 2015; Sony & Naik, 2019, 2020). The end-to-end integration invokes the principle of systems theory, pursuing optimization based on systemic consideration of the whole to achieve results that would be impossible with a reductionist improvement of parts (Bar-Yam, 2018). Prior digital transformation of aspects of the enterprise with information technologies left the machine parts analog and isolated from other parts (Borlase et al., 2017; Garimella, 2018). Industry 4.0 uses cyber-physical integration to enable this holistic system integration and optimization (Saldivar et al., 2015; Salkin et al., 2018). This integration facilitates smartness, the system optimization method based on applying intelligence (Zuehlke, 2010). Industry 4.0 is, therefore, the optimization of the production enterprise using smartness. Researchers have argued that firms do not know where to start this transformation journey and hence cannot chart the path to expected outcomes effectively and efficiently (Machado et al., 2019). This study uses qualitative and quantitative research to develop and validate a model based on empirical evidence to chart the path from technology to business value delivery and facilitate value creation through Industry 4.0.

1.2 Background

Industrial organizations could function with an entirely new paradigm – smart production, by integrating advanced digital technologies with production processes - ***Industry 4.0*** or the fourth industrial revolution (BMBF, 2014; Lichtblau et al., 2015). Industry 4.0 has been understood in different contexts. It is often viewed as the Fourth Industrial Revolution (4IR), a global concept that describes the state of value creation in society in contrast to three prior industrial revolutions (Schwab, 2017). It has also described industrial digital transformation, a phenomenon of the 4IR which focuses on transforming industrial production processes using digitalization and constrains the value creation paradigm within industries and organizations (Ustundag & Cevikcan, 2017). Other perspectives of Industry 4.0, like the Industrial Internet of Things (IIoT) (Malik et al., 2021) and Industrial Internet (Sendler, 2018), are technological concepts focused on digital technologies as enablers of cyber-physical systems (CPS), integrating the physical and digital elements of production at a predominantly production process (sub-organizational) level.

Each industrial revolution uses unique technological functions to transform the production system and improve performance. Machine power, automation, and information management were used for production improvement from the first to the third revolution. Industry 4.0 uses smartness for system optimization; thus, smartness is central to it (Lichtblau et al., 2015). It seeks to induce or increase smartness in the factory (Radziwon et al., 2014), supply chain (Wu et al., 2016), and product (Nunes et al., 2017; Salkin et al., 2018). Smartness is the function optimization quality of systems built on stimuli-responsiveness and intelligence. Industry 4.0 uses smart functionalities to optimize decision-making and automate production processes for performance improvement in production systems. Smartness, including in engineered systems, is difficult to characterize or measure (Alter, 2019). It is noteworthy that smartness is referenced broadly and has been used to describe devices, processes, infrastructure, businesses, and even people. A better understanding of smartness with a definitive framework for developing smart systems will advance the cause of industry 4.0. One of the objectives of this research is a smart systems specification that facilitates an Industry 4.0 maturity model built on assessing enterprise smartness as an outcome measure.

Optimizing the value chain entails achieving outcomes on a range of metrics that address the multiple objectives of the industrial value chain stakeholders. While traditionally, performance measures have focused on commercial metrics, the rise in environmental awareness elevates the focus on sustainability (Baier et al., 2020). The underlying principle is for metrics to be based on broad considerations of stakeholders and their interests in the enterprise's activities (Harrison & Wicks, 2013; Laplume et al., 2008). This research determines Industry 4.0's performance metrics that reflect the holistic implications of end-to-end digital transformation of Industrial value chains for its stakeholders.

Organizations develop capabilities for market differentiation and competitive advantages (Teece, 2019; Teece et al., 1997). Therefore, managers must link Industry 4.0 to its value proposition and embed it in the firm's business and technology strategies. Industry 4.0 is experienced in the production enterprise as a set of capabilities. The Industry 4.0 challenge involves developing and managing these capabilities. Measurability enables management (Drucker, 2012; Earll et al., 2000): yet capabilities are challenging to measure. The lack of proven methods for quantifying existing capabilities, setting the desired target state, and modeling the roadmap between the two positions is also a challenge that maturity models address (O'Donovan et al., 2016). This study develops an appropriate Industry 4.0 maturity model to facilitate its measurement and evaluate its value proposition.

1.3 Theoretical foundation

The study integrates systems theory, dynamic capabilities theory, and maturity modeling to advance the literature on digital transformation.

1.3.1 Systems theory

Systems are a collection of connected components, considered a holistic entity that produces more value than the sum of its parts (Bar-Yam, 2018; Simon, 1991; Teece, 2018). Systems address the collective functionality of components to achieve objectives in ways that individual components cannot, and as such, they represent the value proposition of complexity (Sturmberg et al., 2014). Systems pervade our environments. Living organisms are systems comprising subsystems including circulatory, respiratory, nervous, and other systems. Organisms in large numbers form an ecosystem which itself is a system. Social environments consist of systems such as transportation which comprises components functioning collectively to move people and materials around, and healthcare systems comprising professionals, infrastructure, and technologies to address the healthcare needs of people. Ultimately, production enterprises are systems that transform materials into products.

By integrating the production organization, end-to-end, Industry 4.0 is leaning into the theoretical foundation of systems. In this vein, we could derive previously unattainable value if we consider the value chain as a whole and avoid production in reductionist terms.

Systems theory posits that systems consist of components that function with the principle of holism – the whole is greater than the sum of its parts (Kast & Rosenzweig, 1972; Von Bertalanffy, 1972). Research has established that the quality of information transparency is a function of the degree of integration with impacts on productivity (Čuš-Babič et al., 2014). The whole production enterprise has better information transparency and hence, better potential for smartness (Brosze et al., 2009), supply chain coordination, and financial performance (Kumar & Ganguly, 2021) than its parts. Therefore, the expectation of production performance improvement because of digital transformation is premised on the benefits of the holistic setup of the production enterprise as posited by systems theory.

1.3.2 Dynamic capabilities

Capabilities are the practical contribution of Industry 4.0 to organizations (Szalavetz, 2019), as the value of technologies is the capabilities they enable. Organizational capabilities describe the organization's capacity to execute specific functions (Collis, 1994). They are organized, repetitive collections of routines (Dosi et al., 2000; Winter, 2003). They embed knowledge assets of the organization and deploy its resources with considerable efficiency (Amit & Schoemaker, 1993; Dutta et al., 2005a; Wang & Ahmed, 2007), contributing to organizational outcomes by enabling the conversion of inputs into outputs (Dutta et al., 2005a).

Strategic management researchers acknowledge that the holy grail of organizational value is guaranteeing continuous future revenue or sustainable competitive advantage (Teece, 2014). It is not sufficient for capabilities to support the current success of the enterprise: capabilities that would facilitate future success are required. The existence of such capabilities is contentious because competitive advantages built on capabilities are vulnerable to the actions of other players, and any claims of sustainability are questionable (Collis, 1994).

Strategic management literature proposes different approaches to building competitive advantage; they include firm positioning (Porter, 1985), resources (Barney, 1991), and capabilities (Teece et al., 1997). These aspects are not mutually exclusive as they involve developing assets with price inelasticity. Also, such approaches are susceptible to changes external to the firm, such as future technological developments and socio-economic pressures. Competitive advantage is not sustainable if it does not foster future viability. The Eastman Kodak Company (Lucas Jr & Goh, 2009) and Blockbuster Inc. (Gershon, 2013) are popular examples of firms that failed because of reliance on unsustainable competitive advantages. IBM, meanwhile, has survived many turbulences through adaptation. They have survived by navigating changes in product focus from their beginnings in mechanical tabulating (Yang et al., 2019). Their adaptability has been attributed to dynamic capabilities (Schoemaker et al., 2018). The dynamic capability concept was first introduced by Teece et al. (1997). It is a firm's "ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997, p. 516). It differentiates organizational routines that confer the firm with the ability to address rapid changes in its environment, giving it a sustainable competitive advantage over ordinary capabilities. Dynamic capabilities achieve price inelasticity through VRIN resources (Barney, 1991; Teece, 2018). VRIN is an acronym for valuable, rare, imperfectly imitable, and non-substitutable. They also achieve future-proofing capabilities through seizing, sensing, and transforming features (Kump et al., 2018). The learning capacity of dynamic capabilities is also highlighted (Collis, 1994).

The value of Industry 4.0 is premised on its impact on production performance (BMBF, 2014). The challenges addressed by Industry 4.0 predominantly affect factors outside of the production environment, including variability in the socioeconomic environment, rapidly evolving customer requirements and the escalating social license requirements for production industries (Aheleroff et al., 2019; Dequeant et al., 2016; Furstenau et al., 2020).

Organizational capabilities that do not address the dynamics of the production environment (non-dynamic capabilities) are thus unlikely to be sufficient. Digital transformation literature posits smartness as the intermediate capability induced in the production enterprise through digital transformation (Lichtblau et al., 2015). Furthermore, it exhibits the features of dynamic capabilities, i.e., sensing, seizing, and transforming through smart systems' stimuli responsiveness-based optimization mechanism (Nguyen et al., 2018; Samimi-Gharaie et al., 2018; Zhao et al., 2018). The utility of Industry 4.0 is thus based on its capacity to deliver a key dynamic capability (smartness) that produces production performance gain.

1.3.3 Maturity modeling

The capacity for measuring an entity improves its manageability (Drucker, 2012). Measuring confers an understanding of progress and facilitates inference of the impacts of activities. Quantifying Industry 4.0 is a complex issue due to the structural complexity of production systems and the lack of generally agreed metrics (Mourtzis et al., 2019). While capabilities are useful in deriving firm performance, they have been difficult to measure independently (Dutta et al., 2005a). Maturity models provide a means of measuring capability. They measure capabilities by evaluating the extent of evolution of the dimensions of the capability (Domingues et al., 2016).

Maturity models define a maturity spectrum, which contains a logical, sequential growth path for each dimension of the target capability (Röglinger & Pöppelbuß, 2011). The movement along the path reflects the degree of sophistication or development of the capability or the particular component being evaluated (Bititci et al., 2014; Nikkhou et al., 2016).

Existing maturity models are not universally accepted. They have been criticized for a tendency to arbitrariness in design. They are also thought to lack empirical basis in core structural specifications frequently (Blondiau et al., 2013), and there can be misalignment between the model and reality, which affects its prediction accuracy (Dikhanbayeva et al., 2020; Mittal et al., 2018).

The application of maturity models usually involves the evaluation of efforts with the implicit assumption that efforts translate to outcomes. An analysis of data from Dikhanbayeva et al. (2020), which compared the major Industry 4.0 maturity models, reveals they predominantly comprise effort-based measures that evaluate inputs to the production processes with an implicit assumption of outcomes. Given that task completion does not guarantee outcomes (Martens et al., 2018), effort measures-based models are skewed to effort rather than outcomes. Therefore, this study expands the underpinning theory of maturity models by incorporating outcome measures. It seeks to improve the practical utility of Industry 4.0 maturity models by developing a model that evaluates enterprise smartness – the intermediate capability outcome of embedding Industry 4.0 technologies in the organization's processes. It also seeks to improve the model's empirical validity by deriving the factors (technology use and enterprise smartness), through qualitative research. Thus, avoiding design arbitrariness and misalignment between model and reality.

1.3.4 Digital transformation

Digital transformation (DX) involves digitalizing business processes with technologies to improve outcomes (Westerman et al., 2011). DX predates Industry 4.0. The third industrial revolution was based on extensive information technologies (IT) deployments, digitally transforming aspects of the production organization with enterprise information (Greenwood, 1997). Industry 4.0, however, extended digital transformation to parts of the enterprise that previously remained analog, i.e., operating technologies (OT) (Garimella, 2018; Hicking et al., 2021). Industry 4.0 equips machines and devices with sensing and actuating functionalities, building a hierarchical structure of digital functionalities from the shop floor to enterprise information systems (Zuehlke, 2010). OT digitization enables IT-OT integration, facilitating the complete digitalization of production processes and end-to-end integration of the enterprise (Garimella, 2018; Hicking et al., 2021; Thames & Schaefer, 2016).

The influence of digital transformation is profound. The influence can be observed from different viewpoints. The first viewpoint is from outside the organization; it changes how customers interact with the organization and its products. From within the organization, it changes business processes and organizational structure. Thirdly, it changes business models – how a business creates and delivers value (Morakanyane et al., 2017; Ziyadin et al., 2019). DX's adoption of disruptive technologies increases productivity, value creation, and social well-being (Ebert & Duarte, 2018). It can initiate profound, fundamental changes in how humans work, live, and socially organize (Gale & Aarons, 2018).

Digital transformation planning involves evaluating the current state, envisioning the target state, and mapping the path from the current state to the target state in a transformation plan (Albukhitan, 2020). Due to increased complexity, the extension of transformation beyond the scope of front-end business processes to the entire value chain increases the challenges of strategizing and value realization. Developing Industry 4.0 capabilities is a complex process that represents a significant challenge to organizations exploring the transformation journey (O'Donovan et al., 2016). This study explores the implication of Industry 4.0 – digital transformation scoped to span the entire value chain – for the production enterprise.

Technology-enabled end-to-end integration of the production value chain implies connectivity that extends beyond organizational boundaries, creating a digital enterprise larger than a physical organization with more comprehensive information transparency (Shukor et al., 2021). Systems theory posits that a holistic consideration of the system produces outcomes not achievable by its parts in a reductionist mode (Bar-Yam, 2018). The digital enterprise, indicative of the holistic production system, is thus capable of performance outcomes not achievable in the physical production organization, representing a part of the value chain. This study aims to explore the value proposition of the digital enterprise by determining the relationship between digital transformation maturity of industrial producers and performance outcomes. According to Dutta et al. (2005a), capabilities are intermediate outcomes in the input-output system. Capabilities are also indicative of the value potential of systems. Industry 4.0 represents an input-output system with technology inputs and performance outputs (Büchi et al., 2020; Dalenogare et al., 2018; Lin et al., 2019). Smartness is the capability developed as an intermediate outcome between integrating technology in production processes and the performance gains experienced in such enterprises (Lichtblau et al., 2015). By establishing the relationships between technology use, enterprise smartness, and performance in industrial production, this study will establish the value proposition of industrial digital transformation and significantly contribute to the digital transformation literature.

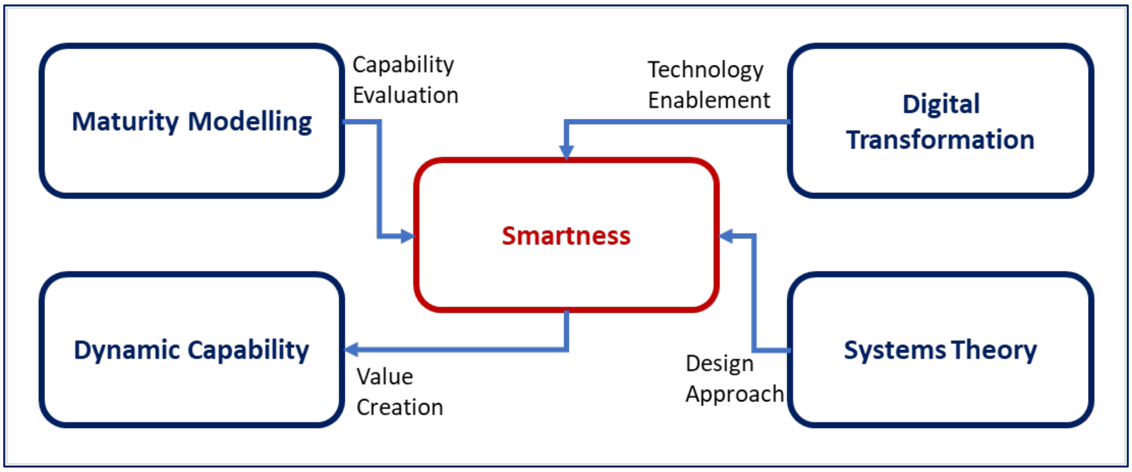

Figure 1-1 - Theory integration

Figure 1.1 depicts the integration of the theoretical foundations with *Smartness*, the central concept of the research. Digital transformation provides the technological enablement for smartness through digitalization and integration of production elements. System theory inspires the design of Industry 4.0 production systems for value delivery by integrating the entire value chain into a holistic system. System theory holds that a holistic consideration of systems is capable of value optimization not possible in a reductionist approach. The holistic approach culminates in smartness through data and information transparency. Maturity modelling facilitates the evaluation of smartness as a measure of Industry 4.0 capability development and dynamic capabilities theory explains how smartness creates organizational value for industrial production.

1.4 Research Question and Objectives

Industry 4.0 is now an important component of production performance improvement strategies (Lee & Trimi, 2021) for its capacity to address the challenges of variability in the production environment, the requirement for greater sustainability of production and the need for product customization (BMBF, 2014; Ghobakhloo, 2020; Jiao et al., 2021; Prause, 2015; Tripathi et al., 2021). The academic discussion on the subject, however, identifies gaps that require addressing, including:

- The continued need for more tools and methods. Studies identified that the journey from concept development to value delivery in Industry 4.0 is challenging and requires improved tools, methods, and frameworks (Machado et al., 2019). There is also a low level of industry adoption of existing maturity and development models, suggesting a need for further developments that better address the practical realities of Industry 4.0 (Felch et al., 2019).
- The need for systems orientation – Industry 4.0 attempts to use a systemic approach to improve production performance. By integrating the production value chain through CPS, it attempts to achieve performance optimization through a holistic consideration of the production enterprise as against a reductionist approach (Fatorachian & Kazemi, 2021; Ghadge et al., 2020). However, many approaches to its implementation are still reductionist in nature as illustrated by the tendency to measure progress based on technology impacts in aspects of the value chain

(Dalenogare et al., 2018; Qader et al., 2022; Szász et al., 2020). An Industry 4.0 framework that embraces systems approach end-to-end is therefore necessary.

- The end-to-end integration of the value chain through CPS is a common narrative for Industry 4.0. However, implementation in practice is often fragmented across the value chain. It requires digitalizing and transforming aspects of the value chain over a significant period. An understanding of the impacts of the different aspects of Industry 4.0 transformation process on across the value chain is necessary for an efficient transformation process.
- While the digital transformation literature posits that there is an expectation of smartness as an intermediate product of Industry 4.0 (Butner, 2010; Chen et al., 2018; Schmidt et al., 2015; Wu et al., 2016), necessary for its performance effect, it does not provide a consistent understanding of the term (Alter, 2019). Its presentation in aspects of literature as a subjective idea of quality also makes it difficult to measure, manage and develop with diminished usefulness in the context of systems. It is therefore necessary to develop a conceptual framework for smartness that facilitates its development and measurement.

While Industry 4.0 represents a specific context of digital transformation or industrial digital transformation (IDT), this thesis uses the terminologies interchangeably. This thesis focuses on the role of Industry 4.0 in organizational performance. This research aims to facilitate digital transformation in organizations by answering an important strategic question: what is the value proposition of Industry 4.0 to industrial organizations? To explore the main research question, the study addresses the following related questions:

1. How does Industry 4.0 create value?
2. What are the organizational features that accompany industrial digital transformation?

3. What technological features play a role in Industry 4.0?
4. What is the role of smartness in Industry 4.0?
5. What is the extent to which technology drives smartness and smartness drives organizational performance in industrial production?

The study addresses the main question by determining the impact of Industry 4.0 maturity on organizational outcomes. In addressing this research question, the following tasks were performed:

1. Develop a conceptual framework for Industry 4.0
    a. Identify generalized Industry 4.0 technological features.
    b. Determine the characteristic organizational features of Industry 4.0.
2. Define smart systems
    a. Classify smart systems.
    b. Identify smart systems characteristics and evaluation parameters.
3. Create an Industry 4.0 business capability model
    a. Determine Industry 4.0 performance metrics
    b. Integrate technology, enterprise smartness, and performance measures in a model for Industry 4.0 value creation process.
4. Evaluate the Industry 4.0 value proposition
    a. Build an Industry 4.0 maturity model based on outcome measures.
    b. Determine the impact of Industry 4.0 maturity on performance.

1.5 Approach

This thesis adopts a multi-method approach that combines qualitative and quantitative empirical methods (Brewer & Hunter, 1989). The multi-method approach is appropriate where an initial study is required to establish the hypotheses for a subsequent study, or a follow-up study is needed to test the results of a prior study (Wood et al., 1999). The complementarity helps enhance the outcomes' validity, a challenge in human-intensive and ICT-related research programs. The emergence of Industry 4.0 in Germany coincided with similar ideas being incubated in other territories, including the USA, the UK, and elsewhere in Europe, creating a vision with uncertain boundaries (Culot et al., 2020). The understanding of Industry 4.0 thus remains fragmented despite receiving significant attention. This study justifies investment in Industry 4.0 capabilities, answering *why Industry 4.0*? To achieve this objective, it uses qualitative research to:

- determine the parameters for assessing Industry 4.0 capabilities in organizations by conceptualizing Industry 4.0 and smartness
- establish the performance metrics for exploring the benefits realization of Industry 4.0.

The qualitative phase explores the knowledge base within the industry, mining its information in natural language form for translation into theory. In this scenario, the participant's expertise is key and semi-structured interviews have been found effective (Sargeant, 2012). Furthermore, they allow for exploring the unique depth of individual respondents' expertise while maintaining consistent coverage across respondents (Saunders et al., 2009). Existential phenomenology is an approach that explores the lived experiences of practitioners for insight and theory development (Collingridge & Gantt, 2008). It is the philosophical foundation for the qualitative approach in this research project. According to Hermann et al. (2016), unlike the previous industrial revolutions observed ex-post, the fourth revolution is managed against set targets by stakeholders. Furthermore, developments in digital transformation have been driven principally by industry actors (Verhoef et al., 2021). The industry knowledge base, therefore, represents a veritable source of information for theory development. The industry's role as the subject matter driver informs the study's qualitative phase. Such scenarios are contextual, and It is implied that a foundation of practical knowledge (distinct from theoretical and productive knowledge) (McKeon, 1941) is required for practical usefulness (Eisner, 1997). This foundation of practical knowledge is important as the study hopes to develop tools with practical relevance in industrial digital transformation.

The quantitative research involved a survey of industrial producers, providing data for measuring their Industry 4.0 maturity and performance based on factors determined in the qualitative study. The quantitative phase of the research aims to validate the research framework developed in the qualitative phase and establish the IDT value proposition by establishing the relationship between Industry 4.0 maturity and organizational performance. Industry 4.0 maturity and organizational performance are both multivariate factors, and establishing causal relationships between multivariate factors in quantitative studies is appropriate for structural equation modeling (SEM) application (Elston et al., 2012, p. 495). SEM represents hypotheses as a model by relating measurement variables to latent variables and latent variables to each other, determining causal relationships (Byrne, 2001, p. 3; Díaz-Chao et al., 2015). By determining the detailed relationships between Industry 4.0 maturity and organizational performance, the study aims to establish the value proposition of Industry 4.0.

Figure 1-2 is the plan for the thesis.

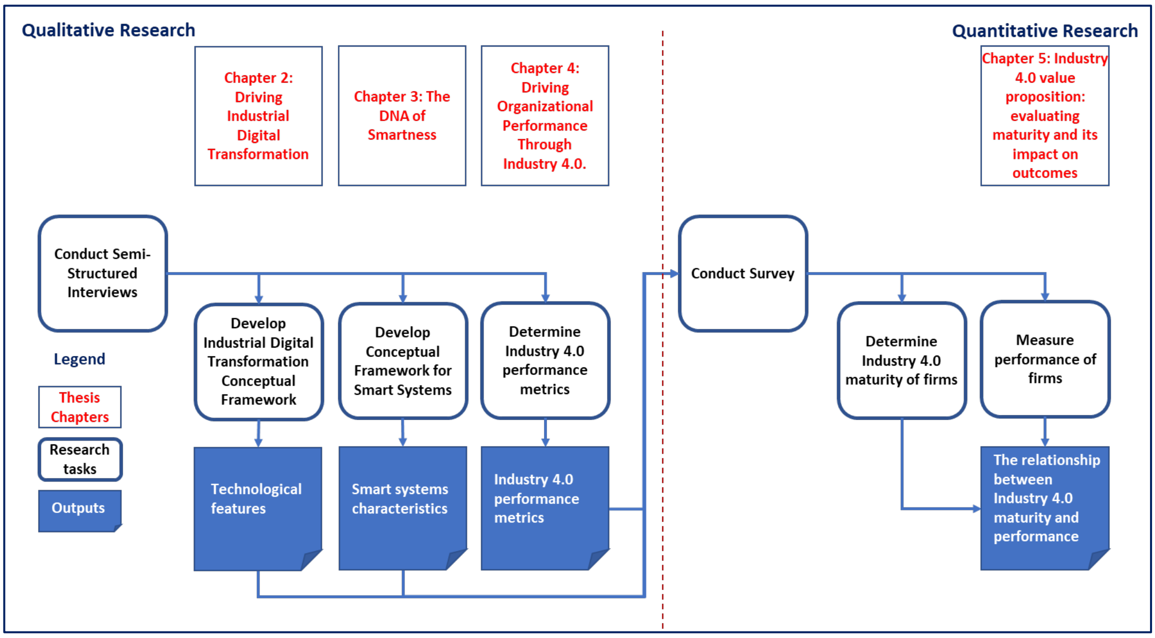

Figure 1-2 - Thesis plan

1.6 Significance of study

While Industry 4.0 has been conceptualized widely as the digital transformation of the end-to-end production value chain for optimization (Lichtblau et al., 2015; Schuh et al., 2017), the outcomes of this study will provide further insights into the nature of this transformation and the justification for it. This study will make theoretical contributions to the Industry 4.0 and digital transformation literature and practical contributions to the industrial digital transformation's technical and management practices. Its theoretical contribution will enable the evaluation of Industry 4.0's value proposition. It will further differentiate the value chain, determining the value proposition of Industry 4.0 in each segment. The maturity model to be developed in this study incorporates outcome measures in addition to the classic effort measures to improve the robustness of the Industry 4.0 maturity evaluation. This model classifies relevant technologies and relates them and enterprise smartness as building blocks for the Industry 4.0 production system and aligns the system with the organizational objectives it addresses.

The study's key implication for practitioners is tooling for aligning Industry 4.0 strategy with organizational goals. The conventional narrative for Industry 4.0 is the end-to-end transformation of the value chain. However, digital transformation is complex, involving complicated decision-making that managers find challenging (Szalavetz, 2019). This study's outcomes will give managers useful inputs into strategy and planning investment decision-making tasks. Similarly, the study will identify technological features critical for Industry 4.0. These will guide policymakers in setting research objectives and their prioritization. The study is also expected to identify the emerging potential for addressing socio-economic issues in wider operating environments of industrial production through digital transformation; these include the impacts on the physical environment, economic growth and the distribution of economic opportunities. These outcomes will provide important inputs into policy-making.

1.7 Thesis structure

The thesis consists of an introductory chapter, a core of four chapters reporting on the research approaches and results, and a conclusion chapter.

Chapter 1 – This is the introduction to the thesis. It lays out the background and identifies the research's theoretical foundations and objectives. It specifies the research approach and plan.

Chapter 2 – This is the first of three chapters based on qualitative research. It addresses the lack of sufficient empirical validity of existing models and their failure to sufficiently mirror reality. It uses data from the semi-structured interviews of experts to develop a conceptual model for driving industry 4.0 capability development. It determined the technology features of IDT as intelligence, simulation, visualization, and remote interaction, data and information management, and stimuli responsiveness. It determined the organizational features as digitization, integration, production ecosystems, persistent customer integration, information transparency, data capabilities, and smartness. It established that Industry 4.0 creates value through these features and integrates them into a framework for driving practical implementation.

Chapter 3 – This chapter uses the data from the semi-structured expert interviews to define a framework for smartness comprising its key characteristics and distinct classes. The key characteristics are stimuli-responsiveness, intelligence, functionality, and optimization. Smart systems functionality is the mechanism for achieving its optimization goals and represents parameters for its qualitative appraisal.

The findings of this chapter identify the parameters of smart systems for evaluating Industry 4.0 maturity, which would inform the instrument later in the quantitative study (in Chapter 5).

Chapter 4 – This chapter used qualitative research to model the Industry 4.0 value creation process in organizations. It builds on systems theory to present a high-level Industry 4.0 enterprise architecture using business capability modeling. The architecture integrates technology, capabilities, and organizational performance, highlighting the mediating role of capabilities in translating technologies into organizational value. It determined four performance factors for Industry 4.0 (productivity, customer experience, sustainability, and safety).

The study identified enterprise smartness as the Industry 4.0 organizational capability through which value is created.

Chapter 5 – This chapter presents the quantitative phase of this research project to test the conceptual model developed in the previous chapters robustly. It aims to provide the link between technology and organizational value in Industry 4.0 and establish its value proposition. The chapter identifies the Industry 4.0 value path from technology use through the smart enterprise to organizational value. It uses factors developed in the qualitative research (technology use, enterprise smartness, and organizational outcomes). The quantitative research uses a survey of 262 manufacturing managers to collect data on manufacturers and builds on and extends the Capability Maturity Model Integration (CMMI) framework to develop a model for measuring the factors. It then employs structural equation modeling (SEM) to determine the relationships between the factors. The study determines that technology use develops enterprise smartness which improves organizational performance. It determines that the path from technology use through production process smartness has stronger value potential than the path through supply chain smartness and product smartness. The study proposes that the value proposition of smart products is industry specific while smart production processes and smart supply chain leads to value irrespective of industry. The differentiated value path from technology use to organizational value provides input into organizational strategy. The study equips production managers with a valuable decision support tool for Industry 4.0 strategy formulation, maturity assessment, and evaluation of transformation initiatives.

Chapter 6 – This is the conclusion chapter. It discusses the research project's outcomes, the management and practical implications, and the theoretical contributions. It synthesizes the results and implications across the study into a global digital transformation model with a detailed reflection of the research outcomes on technology use, organizational features and capabilities, organizational performance, and management implications. This chapter also suggests future research directions emerging out of this project.

2 DRIVING INDUSTRIAL DIGITAL TRANSFORMATION

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2.1 Abstract

The fourth industrial revolution has increased focus on industrial digital transformation (IDT) for its industrial value creation potential. However, practical implementation continues to require improved support from tools and frameworks. This research develops an empirically based conceptual framework for IDT. The study utilizes semi-structured interviews with technology experts, building on and extending the dynamic capabilities theory as its theoretical foundation to identify how IDT uses technologies to create organizational value via smartness capability. The results identify four groups of technological features that support enterprise smartness (1. intelligence, 2. simulation, visualization, and remote interaction, 3. data and information management, and 4. stimuli responsiveness) and the organizational features that characterize IDT, including digitization, integration, persistent customer engagement, production ecosystems, data capability, information transparency, and smartness. The framework identifies that transformation results in organizational value creation. The study's implication for professionals is to re-focus IDT strategy on developing value-creating capability in the enterprise.

Keywords: digital transformation, smartness, Industry 4.0, capability development

Article classification: Research paper

2.2 Introduction

Production organizations are pressed to optimize, in response to increasing requirements for sustainable business (Furstenau et al., 2020), changing needs of consumers (Aheleroff et al., 2019), and variability in the production environments, including through socio-economic crises (Dequeant et al., 2016; Okorie et al., 2020). Industry 4.0 promises to address production optimization challenges through smartness, introducing autonomy and flexibility in production systems (Bartodziej, 2017; Fragapane et al., 2020). Applications include repurposing infrastructure for crisis response, mass customization of products (as production systems can handle a batch size of one), and autonomous response to disruptions in the production value chain. A convergence of technological developments enabled commercially viable cyber-physical systems and created an entirely new production phenomenon. The developments include innovations in sensors that miniaturized and reduced their power consumption, advancements in artificial intelligence, extended reality, cloud computing, and collaborative robotics.

Industrial digital transformation (IDT), Industry 4.0, the Industrial Internet, and the Industrial Internet of Things (IIoT) are often used synonymously (Malik et al., 2021; Oztemel & Gursev, 2020; Ustundag & Cevikcan, 2017). They are associated with the fourth industrial revolution (4IR), where industrial processes are digitally transformed by technologies that implement cyber-physical systems, integrating the production value chain and indicating smartness in the production enterprise (BMBF, 2014; Schuh et al., 2017). While the 4IR is about digital transformation, industrial revolutions are not generally about digital transformation. Industrial revolutions involve the emergence of new production paradigms based on technological developments. The first revolution was achieved using steam power to drive mechanical production functionalities (the factory). It moved production from being bespoke artisan-driven into a predominantly uniform operation that could be accomplished faster by comparatively less-skilled workers (Crafts, 2011). The second revolution enabled mass production using electrical power and electronic functionalities. The third revolution utilized information systems based on computer technologies to drive information-led production capabilities. The fourth uses cyber-physical systems (CPS) to enable smart production capabilities (Drath & Horch, 2014; Schwab, 2017). With each revolution, there is progressively less reliance on labor for the skill and intelligence required to perform tasks. Machines and devices have taken over more production functions. Also, with the advent of Industry 4.0 and the associated smart systems, capabilities for flexibility at scale in product design and production are now realizable. This flexibility at this scale was impossible in previous iterations, and producers can increasingly accommodate product customization requirements (Zhang et al., 2019) and even personalization (Wang et al., 2017). Product customization is in stark contrast to Henry Ford's comment that customer could have their car in "any color so long as it is black" (Ford & Crowther, 1922, p. 72). Although there is some dispute as to if Ford's comment was in jest, it does encapsulate the reduced flexibility and increased uniformity indicative of previous industrial revolutions. This study focuses on IDT as a generalized concept.

The 4IR employs IDT to optimize the production value chain (Lichtblau et al., 2015; Nagy et al., 2018), and Industry 4.0 has been used synonymously with both 4IR and IDT (Gigova et al., 2019; Schwab, 2017). This study presents the IDT perspective, focusing on its organizational capability developing capacity (Szalavetz, 2019). IDT, as a capability development mechanism, represents a business value opportunity for organizations (Talaja, 2012; Teece, 2019), which is the study's focus. The study aims to explore the value creation process of IDT, determining the impact on organizations, including how they develop relevant capabilities. Furthermore, the lack of tools and formal models for coordinating the transformation process has been identified as playing a role in the challenges of developing IDT capabilities for organizations (Wang & Wang, 2022). The study further aims to develop a conceptual framework to aid the IDT process in organizations. The effectiveness of many

IDT models in practice is impacted by a poor reflection of reality (Mittal et al., 2018). Models should sufficiently represent reality because "the major epistemic virtue of successful models is their capacity to adequately represent specific phenomena or target systems" (Poznic, 2016, p. 1). Conversely, models should not be excessively abstract or complex to be overly cumbersome to implement correctly. This study contributes a model of IDT, with an empirical basis, derived from canvasing experts with a holistic view of optimizing the industrial value chain. This study's model aims for simplicity of application while retaining sufficient fidelity to be impactful practically. It considers the essence of IDT and answers the ***what*** question by characterizing the enabling technologies and the functional attributes of the transformed production enterprise.

Defining the IDT conceptual framework would benefit from identifying its technologies based on high-level functional attributes rather than individual listings. The specific set of technologies required is, however, not clearly defined or as obvious as in the earlier revolutions, i.e., first (steam power), second (electrical power), or third (computing) industrial revolutions (Xu et al., 2018). Furthermore, it is reasonable to expect the applicable technologies to evolve, given the pace of technological development and further development in industrial revolutions to Industry 5.0 and beyond (Østergaard, 2018; Xu et al., 2021).

Therefore, this study aims to develop an IDT conceptual framework that answers the following questions:

1. How does digital transformation create organizational value? - What are the feature developments within the organization in the process of IDT-related value creation?
2. What are the key technology groupings relevant for IDT that facilitate avoidance of exhaustive listing of applicable technologies?

2.3 Literature Review

2.3.1 Digital transformation

Digital transformation (DX) is a process for increasing productivity, value creation, and social welfare by adopting disruptive technologies. It alters organizations by digitalizing business processes using information systems (Ebert & Duarte, 2018; Högberg & Willermark, 2022). Digitalization and digitization are used as synonyms in this study. They both refer to the conversion of analog entities to digital. While digitization applies to raw data, digitalization applies to more complex structures like business processes. Digitalization also refers to adopting digital technologies for socio-economic purposes (Brennen & Kreiss, 2016; Schumacher et al., 2016). Digital transformation alters the organizational structure to create more agile and responsive structures (Lee & Edmondson, 2017). The resultant organization is less hierarchical and siloed; it aims to enable a service brokerage orientation in multiple directions, enabling the flow of information and services across the enterprise. DX creates or promotes new influential roles (Singh et al., 2020) that encourage innovation and change. It changes the culture, incorporating higher risk-taking, collaboration, experimentation, and change acceptance (Kane, 2019). It changes its value creation processes (business model), replacing or augmenting products with services (servitization) (Kryvinska & Bickel, 2020) which is a source of longer-term competitive advantage (Linde et al., 2021) and exploiting organizational data assets for commercial value (Barrett et al., 2015). An important feature is transforming the mode of customer interactions with the organization's services through digital channels (Curi & Casquino, 2022; Hansen & Sia, 2015; Mangalaraj et al., 2021). DX also has negative organizational impacts. It has increased employees' anxiety about being replaced by machines (Rampersad, 2020), trust issues in virtual teams (Hacker et al., 2019), and employee change fatigue (Bruce & English, 2020; Nadkarni & Prügl, 2021) with mental health implications. The challenges create the latitude for improvement and the need for more research in the DX space.

Impacts of digital transformation on industries include improved productivity in manufacturing (Davis et al., 2015; Randhawa & Sethi, 2017), higher quality patient care and business efficiency in healthcare (Haggerty, 2017), improved access and new learning functionalities in education (Bilyalova et al., 2020), better product quality, higher productivity, improved working conditions and safer decisions in industrial production (Fonseca et al., 2021), and stimulation of economic growth through smart cities (Tyagi et al., 2019).

IDT is a unique form of DX, extending transformation across production value chains, end-to-end, using cyber-physical systems (CPS) (Salkin et al., 2018). CPS bridges the information exchange gap between physical and virtual elements of production networks. It removes the constraint on information transparency and improves the organization in aspects such as productivity (Horvat et al., 2019), the ability to handle uncertainty (Rüttimann & Stöckli, 2016), and meet environmental and social responsibilities (Ghobakhloo et al., 2021).

2.3.2 Dynamic capabilities

Embedding digital technologies in industrial production processes enables new organizational capabilities; these capabilities are the basis for IDT's value proposition (Szalavetz, 2019). Organizational capabilities are a collection of repeatable routines that enable it to execute specific functions, giving it the capacity to deliver value and transform its inputs into outputs (Collis, 1994; Dosi et al., 2000; Winter, 2003). Capabilities also represent intermediate outcomes for organizations as they transform inputs into outputs (Dutta et al., 2005a).

The theory of dynamic capabilities has links to the theory on the Resource Based View (RBV) for the firm (Teece, 2018). Under RBV, an organization should identify and make use of resources that are valuable, rare, difficult to copy, and non-substitutable to gain competitive advantages and generate abnormal profits (Barney, 1991; Barney, 2001).

Dynamic capabilities further build on and extend RBV in versatile environments. Ordinary capabilities are not guaranteed to sustain an organization's competitive advantage (Teece & Pisano, 2003). They are susceptible to factors external to the firm, including technological developments and strategic challenges from competing firms. Firms can sustain such advantages through dynamic capabilities that enable them to sense and seize emerging opportunities by transforming their resources (Teece, 2018). Furthermore, Teece (2018) argue that dynamic capabilities satisfy the requirements of valuable, rare, imperfectly imitable, and non-substitutable (VRIN) resources for competitive advantage, as defined by Barney (1991).

Smartness is such a capability. It is created in industrial production by digital transformation through integrating the production value chain and enabling information transparency. The enterprise can sense and seize opportunities and transform its processes and resources through intelligence-backed stimuli responsiveness functionalities (Fragapane et al., 2020; Radziwon et al., 2014).

This study proposes that IDT creates value for industrial organizations by generating enterprise smartness as a set of dynamic capabilities that enhance performance, including productivity, customer experience, product, and business model innovation, supply chain performance, sustainability, and occupational health and safety (Bragança et al., 2019; Fonseca et al., 2021; Goryachev et al., 2013; Sinha & Roy, 2020).

2.3.3 Industrial Digital Transformation (IDT) conceptual framework

Conceptual frameworks are useful in scientific studies. They present and narrate important factors, variables, and relationships that define a concept (Miles & Huberman, 1994). They are mechanisms for presenting complex entities. They provide lenses for addressing challenges related to that entity (Bordage, 2009). The approach to capability development is a key IDT challenge to industrial organizations (Lucato et al., 2019; Machado et al., 2019), as such conceptual frameworks could serve an important purpose. Industry 4.0 maturity models are a rich source of IDT conceptualizations. Conceptualizations of IDT underlying maturity models are mostly linear (De Carolis et al., 2017; Ganzarain & Errasti, 2016; Leyh et al., 2016). They present IDT as developments on a single plane. They determine parameters that define IDT and whose graduation on a linear scale reflected the development of associated organizational capabilities. These models have been built around quantitative measures of management and technical competencies or sequentially graduated capabilities deemed to be dimensions of Industry 4.0 (De Carolis et al., 2017; Ganzarain & Errasti, 2016; Leyh et al., 2016; Lichtblau et al., 2015; Rong & Automation, 2014; Schuh et al., 2017). These ideas illustrate simple, intuitive, and process-focused approaches. However, they are often not reflective of the realities of practical business scenarios (Mittal et al., 2018).

An approach to developing an IDT conceptual framework is integrating existing technologies with IDT design considerations. Salkin et al. (2018) proposed a framework based on design principles identified by (Li et al., 2015). Design or architecture principles are critical to defining system architecture; they describe the essential aspects of the system design and provide the necessary guide for its management (Greefhorst et al., 2013). Principles relate the system's high-level strategies to its practical design, ensuring its design and evolution track its objectives. They are critical for presenting the essence of system design (Greefhorst & Proper, 2011). The Salkin et al. (2018) model adopted the design principles of Li et al. (2015), including real-time data management, interoperability, virtualization, decentralization, agility, service orientation, and integrated business processes.

Similarly, Zheng et al. (2021) integrated identified technologies with manufacturing company processes. This approach seeks to identify how technology creates practical value in advanced manufacturing and could present a pragmatic framework for industrial development. However, the lists of technologies, principles, and processes employed in such models are not exhaustive. Consequently, a research process for deriving generalizable insights on IDT strategy and value proposition based on them is challenging. While the technologies are widely referenced in digital transformation literature, they acknowledged that the list is not exhaustive. Furthermore, the design principles are not universally agreed upon (Dikhanbayeva et al., 2020; Habib & Chimsom, 2019).

This study is critical in addressing the gap in IDT conceptual frameworks in the digital transformation literature. The development of IDT-related organizational capabilities is challenging in practice, practitioners have difficulty determining the starting point and charting the course to value delivery, and the requirement for improved tools, methods, and frameworks remains (Machado et al., 2019). Furthermore, the low level of industry adoption of the maturity and development models based on existing conceptualizations suggests that further improvements that reflect the practical realities of Industry 4.0 scenarios are useful (Felch et al., 2019). Therefore, there is a need to take another look at the conceptualization of IDT with a sufficient representation of practical scenarios for business usefulness. The conceptualization should have empirical validity to support research activities and address the gap between digital technologies integration in production processes and industrial value creation.

2.4 Research Method

The methodology for the study comprises semi-structured expert interviews. Semi-structured interviews are effective where the respondents have significant objective knowledge of the subject matter (McIntosh & Morse, 2015). The study follows the approach of existential phenomenology, exploring the experiences of members of a group to gain their perspectives to facilitate theory development (Collingridge & Gantt, 2008). Interviews are particularly appropriate in this scenario. Appendix A contains the interview questions framework. Sixteen highly experienced digital transformation professionals from seven organizations with expertise in IDT were interviewed. The group comprises senior members of top global firms' digital transformation and technology advisory functions by revenue (Statista.com, 2020), they all have responsibility for delivering their client's critical digital transformation objectives. The study employed snowballing sampling (Etikan et al., 2016). Respondents were encouraged to facilitate the participation of their colleagues in the study. The top global technology service providers involved in providing technology for digital transformation were approached, from where a snowballing technique was deployed. Senior management personnel of global businesses is an elusive target group, and snowballing facilitated multiple respondents from organizations which helped triangulation for research quality (Kitto et al., 2008).

According to their financial reports, the smallest of the firms by annual revenue had over USD 30B in revenue in 2021. The respondents had a minimum of twenty-one years of technology and management experience and were based in Australia, the USA, the UK, France, and Singapore during their interviews. The profile of respondents, particularly the length of their industry experience, improves the chances of expansive views acquired from different organizations they have worked. Their overall career experience spanned many more countries, including India, Nigeria, Germany, Brazil, China, The Netherlands, and South Africa. The profiles of respondents are presented in Table 2-1. The interview questions guide was shared with participants before the interviews to allow them to prepare adequately for the interviews. The questions involved digital transformation, smartness, and technology-related organizational capabilities. They were also asked about perceived benefits, hindrances, and enablers of these capabilities.

Responses to questions and further elaborations were recorded, coded, and analyzed for theory development on Industry 4.0, what it is, how it is achieved, and why it is done. Coding and analysis followed the Gioia methodology (Gioia et al., 2013). It has been used effectively for contextual analysis in qualitative research (Gehman et al., 2017), which is at the core of this study. Furthermore, it identifies the aggregate dimensions of the subject in very short iterations, which lends itself to applications in conceptual framework development. The Gioia methodology establishes the underlying structure of the research concept through a uniform process that allows consistent treatment of participants who may not have been interviewed at the same time, enabling the recognition of convergence at a point where new emergent concepts are no longer observed. According to Gioia et al. (2013), researchers must constantly cycle through concepts and emergent themes to determine if new concepts are discovered. For this study, convergence was achieved after 16 interviews.

The Gioia methodology consists of three stages, the first-order analysis, the second-order analysis, and the aggregate dimensions (Gioia et al., 2013). The first-order analysis consists of *open coding* (Strauss & Corbin, 1998). The researcher captures the participant's thoughts as originally as possible, identifying concepts that emerge directly from the participant's words. The first-order concepts feed the second-order analysis with a relatively large number of concepts from which the researcher identifies emerging orders, groupings, and associations, names them, and arrives at a reduced number of concepts as the second-order concepts. The researcher then embarks on another iterative process, applying the lenses of applicable theory to the second-order concepts. In this study, the foundational theory is dynamic capabilities. We posit that technology represents inputs into the IDT process that generate organizational value as outcomes via organizational capabilities. We apply this lens to reviewing the second-order concepts and observe emerging concepts representing the inputs, outcomes, and intermediate changes to the organization as aggregate dimensions. *Appendix J – Data Structure* maps the concepts across the analysis iterations, presenting the final dimensions defining the digital transformation process.

The study considered critical issues in research quality (Golafshani, 2003; Rolfe, 2006). They ensure that research instruments measure the concepts they purport to measure and do so accurately. Research quality was addressed in multiple ways. Firstly, there was expert validation by research colleagues (Straub, 1989). The experts consisted of research colleagues with extensive experience in digital transformation and qualitative research who provided inputs for refining the question framework. Secondly, triangulation is a viable method for addressing validity (Kitto et al., 2008). This study deployed triangulation by having multiple respondents across industry segment expertise and within firms and applying the interpretative rigor of three researchers for reviewing the emergent data structure from the coding and analysis of responses (Kitto et al., 2008).

Respondent	Location	Years	Education	Principal Industry Expertise
1	Australia	29	BA	Government, Natural Resource
2	Australia	30	BA	Government, Natural Resource
3	Australia	28	M.Sc	Aerospace
4	Australia	33	B.Sc	Industrial, Utilities
5	France	34	B.Eng	Industrial
6	USA	31	MBA	Automotive
7	USA	35	MBA	Utility, Natural Resources
8	Australia	20	M.Sc	Exploration
9	USA	23	B.Eng	Automotive
10	USA	27	PhD	Industrial, Supply Chain
11	USA	25	MA	Industrial, Supply Chain
12	USA	21	MBA	Industrials, Automotive, Pharmaceuticals
13	USA	25	BA	Industrial
14	Australia	25	B.Eng	Industrial
15	Singapore	36	B.Com	Government, Healthcare
16	USA	29	B.Sc	Technology, Media, Telecommunications

Table 2-1 - Participant's profiles

2.5 Results

We derived first-order concepts, second-order concepts, and aggregate dimensions by applying the methodology to the data collected from the respondents. The aggregate dimensions are the technology and organizational features.

Appendix B maps the first-order concepts to second-order and second-order concepts to the aggregate dimensions.

2.5.1 Technological features

Analysis of the research data revealed four classes of technological features. These groups broadly address key requirements of smart production systems. They are intelligence, simulation, visualization, and remote interaction, data and information management, and stimuli responsiveness.

2.5.1.1 Intelligence

Seven of the 16 respondents (4, 5, 7, 11, 13, 14, and 16) identified machine Intelligence as an essential feature of IDT as it is critical for smart systems. Respondents 7 and 13 further noted that artificial intelligence is a part of a collection of technologies that collectively create unique emergent characteristics of IDT. According to Respondent 7, *"Industry 4.0 capabilities are facilitated by advanced technologies that enable stimuli responsiveness, artificial intelligence, data processing, visualization, and robotic actuation."*

Technologies noted by respondents in this category include machine learning, natural language processing, machine vision, and predictive analytics.

2.5.1.2 Simulation, visualization, and remote interaction

Respondents 3, 4, 13, and 16 recognized the importance of technologies that facilitate simulation, visualization, and remote interaction for IDT. According to Respondent 3, Extended reality (XR) enables remote interactions between users and production elements (systems and processes) by removing boundary constraints. They note that removing boundary constraints is a defining characteristic of post-Industry 4.0 industrial operating environments. They stated, *"Development in cybersecurity and extended reality suggests that removal of environmental boundary constraints is key to Industry 4.0 and might define its evolution into Industry 4.1 or even 5.0"*. Respondent 4 identified the role of Virtual Reality (VR) in Operating Technology (OT) digitization, IT-OT integration, and the importance of simulation and visualization capabilities of digital twins in Industry 4.0-related advanced product development capabilities. XR is identified as one of the technologies that create the integrative property of CPS (Respondents 13 and 16), enabling the integration of virtual and physical production components. Technologies in this category referenced by respondents include augmented reality, virtual reality, live virtual construct / mixed reality, and digital twins.

2.5.1.3 Data and information management

Respondents 1, 5, 7, 13, 14, and 16 identified digital infrastructure (DI) for data and information management is key for IDT. According to Respondent 7, data processing is an underlying requirement of IDT, hence the requirement for acquiring, storing, processing, securing, communicating, and transporting data. Respondents 5 and 14 identified computing infrastructure as key for Industry 4.0. These are not new to organizations, being the hallmark of the third industrial revolution, predating Industry 4.0. According to Respondent 3, *"the previous revolutions had pockets of gains in automation and computing."* Industry 4.0, however, builds on developments in DI, like cloud computing, combined with advancements in other technology areas to create smart solutions (Respondents 1, 5, and 13). Respondent 14 further recognized infrastructure democratization as a social value created by Industry 4.0 and enabled by cloud technology. According to Respondents 1 and 16, Industry 4.0 capabilities require next-generation data communication functionalities featuring hyperconnectivity and high throughput, low latency communication. Overall, technological capacities for acquiring, processing, securing, transporting, and storing data and information, including enterprise information systems, cloud computing, edge computing, 5G networks, cyber security, and data analytics, were identified as key for IDT.

2.5.1.4 Stimuli responsiveness

Sensing and actuation are considered in tandem because they combine to give systems stimuli responsiveness functionalities, enabling systems to interact with their environments. Four respondents (4, 7, 13, and 14) identified the role of sensing and actuation. Respondent 7 stated, *"Industry 4.0 capabilities are facilitated by advanced technologies that enable stimuli responsiveness"*. Respondent 4 identified sensors and the ability to measure physical processes within the environment as one of the key underlying technologies without which

Industry 4.0 would not be possible. Sensors accomplished this by enabling the digital transformation of OT (operating technologies). Respondent 14 singled out changes in the working of machines due to advancements in sensor technologies as an important enabler of Industry 4.0.

Production systems respond to their environments using actuation technologies. According to respondents 4, 7, 9, and 14, advanced robotics is an important actuation mechanism in Industry 4.0. Respondents recognized the importance of cobots, industrial robots, and Automated guided vehicles (AGVs).

2.5.2 Organizational features

The results identified the following defining organizational features enabled by Industry 4.0.

2.5.2.1 Digitization

Eleven of the respondents (1, 4, 5, 6, 7, 8, 9, 10, 11, 12, and 14) identified the role of digitization as the base concept of Industry 4.0. Respondent 8 viewed digitization as definitive of Industry 4.0; according to them, *“Industry 4.0 is the digitization and integration of the entire production enterprise to deliver an end-to-end digital value chain*.” The unique importance of digitizing OT or machines to Industry 4.0 is a running narrative across the respondents on digitization. Respondents 4 and 10 noted that OT digitization is a niche functionality of Industry 4.0. They proposed that OT digitization extends prior digitization of the front office with Information Technology (IT). Respondent 10 stated Industry 4.0 included the *“Fusion of IT and OT, or the digital and physical components of production (with IoT) to create new socio-economic values.”* The digitization of OT is distinctive and significant as it enables IT-OT integration to facilitate the 360-degree flow of data between the cyber and physical components, thus enabling the Cyber-Physical System (Respondent 4).

2.5.2.2 Integration

Integrating the production enterprise as an objective of Industry 4.0 was highlighted by the majority of respondents (3, 4, 5, 6, 7, 8, 11, 12, 15, and 16). Along with digitization, Respondent 8 considered integration as definitive of Industry 4.0. According to the respondents, the context for integration in Industry 4.0 covers all production entities to achieve end-to-end integration. Cyber-physical integration is, however, the characteristic feature of Industry 4.0, according to Respondents 9, 10, 12, and 13, as it enables the networking of physical and virtual elements, enabling a physical-virtual information loop. On the enterprise level, CPS achieves IT-OT integration, which according to Respondent 10, enables the delivery of socio-economic values.

Industry 4.0 builds on CPS to create a non-linear value chain through horizontal, vertical, and end-to-end engineering integrations. According to Respondent 16, integrated value chains create capabilities not seen in linear value chains. Relating the value proposition of Industry 4.0 directly to CPS, Respondent 3 claimed, *“Industry 4.0 is revolutionary, resulting in efficiency and effectiveness gains through CPS.”* Similarly, according to Respondent 9, the enhanced production capabilities of Industry 4.0 are associated with cyber-physical integration. The advanced capabilities emerge through the enablement of seamless man-machine interaction, process digitization, and data transparency. Respondent 13 notes the attribute of the transformation induced by CPS to include speed, transparency, visibility, autonomy, and flexibility.

2.5.2.3 Data capability

Seven respondents (4, 5, 7, 11, 12, 13, and 14) highlighted the importance of data to Industry 4.0. According to Respondent 11, *“data is the lifeblood of Industry 4.0”*. The respondents addressed the data capability of production organizations in acquiring data, processing data, and using assets data for business intelligence and digital enablement. Respondents 4 and 14 discussed the role of sensors in deepening the data acquisition capacity of production systems as important for Industry 4.0. Respondents 7 and 11 elaborated on the role of digital infrastructure for data processing, storage, and transport, and respondents 5, 11, and 13 pinpointed digital infrastructure's role in analytics and business intelligence. According to Respondent 12, Industry 4.0 business models exploit data commercially.

2.5.2.4 Production ecosystems

Respondents 1, 11, and 15 described the emergence of production ecosystems from the integrated value chain. According to Respondent 1, interoperability facilitates ecosystem formation. The respondent predicted shifting production value chains away from tight integrations towards more agile, ecosystem-friendly approaches. According to Respondent 15, the integrated ecosystem approach delivers superior production value than the unintegrated enterprise. They stated: *"Industry 4.0 uses the connectedness of systems and processes across the entire production value chain to create an intelligent, flexible production ecosystem, delivering superior value compared to the unintegrated enterprise."* To highlight the value proposition of ecosystems, Respondent 11 associates the smart characteristics of Industry 4.0 production enterprises with the flexibility of the ecosystem approach.

2.5.2.5 Information transparency

Seven respondents (3, 7, 9, 10, 11, 13, and 16) identified information transparency as key to Industry 4.0. According to Respondent 10, the value of Industry 4.0 relates to its role in completing the information loop started in Industry 3.0. They stated: *"The fourth revolution completes the digital-physical loop by feeding back analyzed information into the physical space from the digital."* According to Respondent 16, it enables the flexibility required for the responsiveness of Industry 4.0 production systems. Respondent 11 associates data access and real-time information availability with smartness. Respondent 3 identified removing boundary constraints to facilitate ubiquitous access to information as a defining feature of Industry 4.0 and beyond. Remote interactions are possible because of the exposure of information beyond the physical barriers of Industry 4.0 systems. Respondent 9 posited that the visibility of data and processes in Industry 4.0 was universal. The respondents connect the relationship between data capability, information transparency, and smartness in the Industry 4.0 context.

2.5.2.6 Persistent customer engagement

According to Respondents 2 and 8, the increasing need to customize products is one of the key drivers for Industry 4.0. Respondents 8 and 16 identified persistent customer engagement as a characteristic of Industry 4.0 aimed at facilitating mass product customization. Respondent 8 claimed that an early engagement of the customer in the production process and continual engagement throughout the product lifecycle is necessary for mass customization. Respondent 16 claimed that producers must have constant visibility of customer behaviors and preferences as an input into the production cycle to fulfill the objectives of Industry 4.0. They state that Industry 4.0 creates a fully integrated enterprise through which *"producers have both visibility of and dynamic insights on their own operations end to end, covering supply chain, customers and production systems, and processes."*

2.5.2.7 Smartness

All respondents except three (Respondents 3, 4, and 10) related Industry 4.0 to smartness. According to Respondent 11, digitization and integration are foundational to Industry 4.0, creating the platform for smartness. Respondent 12 claimed that industry 4.0 technologies are associated with smartness, and transforming the production enterprise into a smart one is a characteristic of Industry 4.0. Similarly, Respondents 2, 6, 7, and 13 identified connections between Industry 4.0 technologies and smartness. Respondents 6, 7, and 13 linked smart system characteristics to digital technologies, and Respondent 2 claimed that the problem-solving capacity of Industry 4.0 is attributable to the smartness of solutions created out of digital technologies and addresses the socio-economic challenges.

The respondents presented smartness as a characteristic feature of Industry 4.0. Respondent 5 identified smartness as the emergent capability of Industry 4.0 through which it creates value. They stated: *“the implementation of these technologies enable the integration of the value chain and the factory elements resulting in three capabilities, smart products, smart factory, and smart supply chain.”* The respondents collectively argued that digital technologies combine to induce smartness in the production processes and the organization’s business functions. Furthermore, they posit that smartness is a means to an end. It provides functionalities that enable the delivery of Industry 4.0’s value propositions.

2.5.3 Value creation

All the respondents identified socio-economic values created by Industry 4.0, demonstrating it is a core outcome or focus for the process. Respondent 1 noted organizational productivity and national economic gains, other value creation identified by respondents included: productivity (respondent 15), cost efficiency (respondent 3), product innovation (respondent 12), customer experience (respondent 6), employee wellbeing (respondent 15), environmental sustainability (respondent 2), sovereign manufacturing capability (respondent 1), social equity (respondent 14), and economic growth (respondent 1). According to Respondent 2, Industry 4.0 emerged to address challenges in three aspects of production - product customization, environmental impact, and increased variability in the production environment. Respondents 2, 8, and 16 claimed that it addresses those challenges. Respondents 7 and 10 indicated that Industry 4.0 is a set of capabilities that deliver optimal socio-economic outcomes in industrial production. Respondent 15 compared the value creation of Industry 4.0 with the unintegrated production paradigm that existed before it and claimed that Industry 4.0 delivers superior value by organizing its integrated production chain into an intelligent and flexible ecosystem.

2.5.4 Conceptual framework

In addition to validating the importance of factors (as discussed in sections 2.5.1 - 2.5.3), Figure 2-1 illustrates these relationships in the conceptual framework developed in this study which will be discussed further in this section.

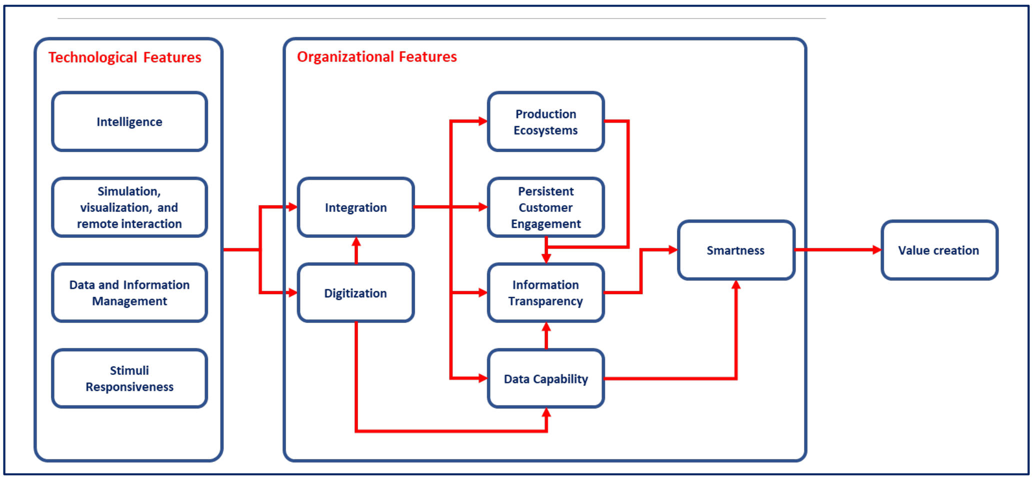

Figure 2-1 - Industry 4.0 Conceptual Framework

The respondents discussed the impact of technology in creating value through a range of organizational features. Respondent 7 attributed the value to multiple functionalities from different technologies, and according to Respondent 13, *"Industry 4.0 happens when several developments in technology are considered collectively rather than individually."*

The basic value of technology is the enablement of digitization and integration (sections 2.5.2.1 and 2.5.2.2). Respondents 8, 11, and 12 simplify many relationships between factors. They established links between integration and customer engagement, ecosystems, data capability, and information transparency. Respondent 11 provided a link between digitization and integration, stating: "*the digitization provides the platform for the integration.*" They identified production ecosystems and customer integration as key integration contexts. Listing key attributes of Industry 4.0, Respondent 11 described Industry 4.0 as: *"the horizontal integration of the production ecosystem,"* and Respondent 8 stated: *"Industry 4.0 integrates the entire value chain and enables the engagement of the customer early in the process and throughout the process."* Respondent 11 links digitization and integration to data capability. They stated: *"digitization and integration are crucial for data capability."* The integration connects production ecosystems and facilitates customer engagement, facilitating information transparency and data capability, leading to smartness in the enterprise.

Respondent 12 stated that the integration *"seamlessly funnels data and analyzed information back and forth between the digital and the physical elements,"* establishing the link between all integrated entities and information transparency. They also attributed the smartness of the enterprise to data capability and information transparency, stating*:*

> *Industry 4.0 ultimately transforms the enterprise into a smart one… The organization exhibits autonomous functionalities and seamlessly funnels data and analyzed information back and forth between the digital and the physical elements to enable further intelligent actions in the physical world. (Respondent 12)*

Respondent 2 attributed Industry 4.0 value creation to smartness. Respondent 2 stated: *"Through smartness, Industry 4.0 addresses the challenges that necessitated it.*

The research thus synthesized the relationships across the factors into the conceptual framework for Industry 4.0:

- Digital technologies collaborate to enable digitization and integration.
- The integration connects customers and creates a connected production ecosystem.
- The integrated ecosystem and customer enable data capability and information transparency, which lead to smartness.
- The enterprise uses smartness to generate socio-economic value.

2.6 Discussion

While there is an industrial revolution perspective of Industry 4.0 with broader implications for society, this study explored Industry 4.0 from an organizational perspective that creates value through digital transformation. The study produced a conceptual framework to drive the IDT process within organizations. The framework provides a pragmatic approach to managing the many technologies, tools, and methods of Industry 4.0 for value creation.

Validating the technologies, tools, and methods of Industry 4.0 is important for implementing the concept, and the digital transformation literature dedicates considerable focus to it (Da Costa et al., 2019). The framework presents technology as inputs into the transformation process and organizational value creation as the outcomes. It focuses on the inputs on the organization between the technology inputs and the value outcomes, initiating organizational features that culminate in smartness and result in organizational value creation.

2.6.1 Technology

According to Respondent 3, some technological features that predate Industry 4.0 play critical roles in IDT. The pace of technological developments also implies that new technologies with IDT relevance will continually emerge. This study, therefore, avoids attempting to identify IDT or Industry 4.0 technologies. Determining Industry 4.0 technologies is also complicated because many ‘technologies’ usually referenced in the Industry 4.0 literature are systems comprising multiple technologies, e.g., additive manufacturing consists of sensors, actuators, AI, and DI. However, the study finds that developing key organizational features and focusing on value creation provides the necessary context for IDT value proposition. IDT technologies conceptually are, therefore, those with unique or significant contributions to smart production and its underlying features, including digitalization, integration, data capability, and information transparency. Given the role of technology in IDT, its framework must reflect technology. This study identifies four groups of technological features that drive the technology application in IDT. Building the model on functional features rather than specific technologies enables a framework with a degree of technology agnosticism.

Smart systems are stimuli-responsive (sensing and actuation) (Zhao et al., 2018), intelligent (Molinara et al., 2021), and have enhanced data capabilities (Ferraris et al., 2019; Habibzadeh et al., 2018; Kernecker et al., 2020; Samimi-Gharaie et al., 2018; Zhou et al., 2019), including digital infrastructure for data handling (Kaltenbrunner, 2017). The IDT context for smartness also has unique requirements for extended reality (Damiani et al., 2018; Sepasgozar et al., 2021; Serras et al., 2020) to facilitate simulation and visualization.

2.6.2 Organizational features

Respondent 11 states that data is the lifeblood of Industry 4.0. Data is a lens through which the Industry 4.0 framework can be understood. Digitization and integration enable Instrumentation, interconnection, and intelligence, which are properties of effective smart systems (Harmon et al., 2015). They facilitate data acquisition, transportation, and utilization, the foundational infrastructure for data management capabilities, and transform the production enterprise into a network of production information systems that facilitates information transparency (Flatt et al., 2016). Information transparency is the basis for smartness by enabling real-time information on production parameters for optimal decision-making and autonomous functionalities (Brosze et al., 2009; Čuš-Babič et al., 2014).

Data is a new source of business value through business model change, enabled by persistent engagement of the customer for customer-driven innovations (Müller et al., 2018). Respondent 12 notes that business model transformation in Industry 4.0 exploits the value of data. It thus transcends enabling the value creation process; it is value itself. IDT promotes the adoption of new organizational business models and embedding new business practices that intend to evolve the organizational efficiency level and simultaneously address social and environmental challenges. Aiming to simultaneously deliver performance and ensure transformation, creating enduring value for its key stakeholders and achieving remarkable results as the EFQM 2020 model advanced. These novel Business Models can add a strategic and technologically unbiased perspective to a technology-centered Industry 4 approach (Fonseca et al., 2021)

2.7 Conclusion

Developing IDT capabilities in production organizations is complex (O'Donovan et al., 2016; Szalavetz, 2019) and often chaotic (Machado et al., 2019). This work offers valuable contributions. It has made a theoretical contribution of an evidence-based conceptual model for driving Industry 4.0 maturity and value creation. This model can serve as a guide for practitioners.

IDT employs digital technologies to enable smartness for outcome optimization. Following the input-output system model of Dutta et al. (2005a), smartness is the value-creating intermediate capability of IDT. The smart enterprise capability is built on information transparency functionality, resulting from digitalizing and integrating the production value chain. Integrating the value chain results in a production ecosystem of multiple partnering firms and the end-to-end embedding of the customer in the product lifecycle, enabling real-time, contextual information on production elements, including people, materials, products, devices, systems, and organizations. Digitization, integration, enhanced data capability, efficient production ecosystem, customer integration, and information transparency are organizational features that signpost the digital transformation process. They are parameters from this study that can help embed an IDT strategy in practical reality, defining a conceptual framework to guide execution and value delivery quality.

2.7.1 Managerial implications

While Industry 4.0 has been conceptualized widely as the digital transformation of the production organization (Lichtblau et al., 2015; Schuh et al., 2017), the outcomes of this study provide further insights into the nature of this transformation for information systems managers and operations managers tasked with introducing industry 4.0 technologies in their workplaces. Previous studies established that Industry 4.0 considerations must expressly cater to business and management elements of transformation beyond technology (Ebert & Duarte, 2018; Issa et al., 2018; Schuh et al., 2017). This study highlights features within an organization that should be targeted for development. Implemented technologies should impact the organization's capacity to digitalize processes and functions, all integrating physical and virtual entities. It should improve the data capability of the organization, including acquisition, management, and utilization. Persistent integration of the customer into the product life cycle and enablement of production ecosystems through interoperability is critical in successful Industry 4.0 implementation.

Technology creates the capability for digital transformation in the production enterprise. It combines functional attributes of sensing and actuation technologies, artificial intelligence, extended reality, and digital infrastructure to create smart solutions that support digitization and integration. The technology implementation must have traceability to smart functionalities in production processes and business functions. Managers must realize that implementing these technologies does not actualize Industry 4.0, and many of these technologies would already exist in the organization as they predate Industry 4.0. The Industry 4.0 strategy must target capabilities by integrating the enterprise end-to-end through digitizing OT and implementing CPS using existing and newly implemented technologies.

Table 2-2 summarizes the managerial implications of factors identified in the research.

Factor	**Implication**
Stimuli Responsiveness	The technology strategy must identify opportunities to sensorize machines and expand IoT. It must identify manual activities and repetitive processes that represent good opportunities for automation.
Data and Information Management	The Industry 4.0 strategy must consider the digital infrastructure's adequacy, flexibility, and optimality. It is foundational to data capability and will perverse the technology landscape. It could drive costs.
Intelligence	Business intelligence and automation requirements should drive Artificial intelligence technologies adoption. Its value should be measured by decision-making accuracy and autonomous functionalities.

Simulation, Visualization, and Remote Interaction	Extended reality technologies should be part of the digitization strategy. Extended reality integration into processes should be driven by requirements from the value end of the strategy, particularly product innovation.
Digitization	Managers should ensure that business requirements drive digitization. The focus of digitization should be on sensorizing machines and automating manual processes. Digitalized business processes and functions should characterize the target state.
Integration	The target state should be characterized by eliminating silos and stand-alone elements in the production process.
Production Ecosystems	The transformation should eliminate all isolated business functions in the production process. Visibility of all entities at all points throughout the value chain must be a goal.
Persistent customer engagement	The transformation must embed the customer's perspective in all phases of the product lifecycle. It must enable customer-driven product innovation.
Information Transparency	Information transformation should be a key driver of strategy. At each point in the strategy, an important question should be, "do we have all the necessary information on all production elements in real-time?"
Data Capability	The ability of the production enterprise to acquire, manage and utilize data. This capability should be driven by a maturity model mapped to the business objectives.
Smartness	All activities in the strategy should have traceability to this capability. Technologies must contribute to stimuli responsiveness, intelligence, decision-making, information transparency, or autonomous functionalities.
Value Creation	Industry 4.0 implementations must be targeted toward specific value creation objectives for the organization. The research identified several social and economic value creation potentials of Industry 4.0, including productivity, sustainability, cost efficiency, social equity, and economic growth.

Table 2-2 - Research factors

2.7.2 Limitations and future directions

The study is designed to produce generalizable results across industrial production; it, therefore, does not explore industry sector-specific insights. Further studies designed to elicit sector-specific insights for industrial digital transformation will be valuable. While the study utilized 16 interviews of respondents from seven organizations based in four countries, a broader scope of organizations and countries and a larger pool of respondents could improve the validity and reliability of the study and hence its generalizability. Furthermore, a quantitative study to validate the outcomes of this study is useful.

This study has produced a model to support managers' Industry 4.0 strategies. It offers aid to information systems managers, digital transformation specialists, and business leaders in charting a pathway from technology implementations to value realization. It focuses its strategy on developing value-creating features in the enterprise, including integrating customers into product lifecycle management end-to-end, enabling an effective production ecosystem, developing the organization's data capability, and developing information transparency and smartness across the value chain. The contribution of this study will help actualize the industry 4.0 vision in practical scenarios.

3 THE DNA OF SMARTNESS

Journal submission: *This chapter was submitted for publication in the Australasian Journal of Information Systems: Abiodun, T., Rampersad, G.C. and Brinkworth, R., "The DNA of Smartness " (under review). The Student's contribution was the majority of the publication (95%), specifically research design, data collection and analysis, and writing. The supervisors had a guiding, review, and editing role (5%).*

3.1 Abstract

The term 'smart' is increasingly used to characterize entities, including devices, systems, organizations, and societies. It has become imperative that smartness be understood and conceptualized with frameworks for management. This study explores smartness based on systems theory in the context of engineered systems answering the questions of what, why, and how. Using a qualitative research process, we deployed semi-structured interviews of experts to translate their lived experiences into theory. The study identified stimuli-responsiveness, intelligence, functionality, and optimization as the four key aspects that characterize smartness and collectively define an identification framework for smart systems. The study also identifies non-smart, semi-smart, and fully-smart classes as the three distinct smart systems classes. A system is non-smart if it lacks defined aspects and semi-smart if its intelligence component is hardcoded, i.e., it does not learn. The study produced a framework that provides a basis for the qualitative evaluation of smartness.

Keywords: Smartness, intelligent systems, optimization

3.2 Introduction

Information systems scholars have not agreed on the definition of smartness (Alter, 2019). The Oxford Learner's Dictionary defines smartness as a quality of clean appearance and a synonym for intelligence. In the innovation and technology management literature, 'smart' is often used to depict something better than what currently exists, such as smart energy characterization as sustainable energy (Corsini et al., 2019). Smartness is also often explained with superior functionalities compared to the smart system's non-smart, legacy predecessor. For example, smart transportation has been described as having advanced functionalities, such as predictive and real-time information to road users on traffic conditions and parking space availability (Habibzadeh et al., 2018). The depiction of smartness in the above context would compromise its application in purposefully designed autonomous systems independent of human control. It also implies that the experience of smartness is a subjective perception of quality with no prospect of an empirical framework and controlled development and exploitation. Such connotations of smartness are vague, trivial, and lack contextual clarity (Alter, 2019). An implication of smartness as merely a subjective idea of quality is that it becomes difficult to measure, manage and develop. Its usefulness in the context of systems development thus becomes severely diminished.

Industry 4.0 literature identifies industrial production transformation into a state called 'smart' as its objective (BMBF, 2014; Lichtblau et al., 2015). Furthermore, the influence of Industry 4.0 goes beyond industrial production. It underpins how humans live in the age of the fourth industrial revolution (Ferraris et al., 2019), including addressing critical global challenges like equality (Golub et al., 2019) and sustainability (Furstenau et al., 2020), making the smartness of systems an essential quality of modern life. Following the expectations of Industry 4.0 for industrial production and wider societal applications, smartness is conceived as an optimization function of systems in this study. Systems with smartness claims pervade our experiences, including phones, cars, public transportation, healthcare, and cities. The questions that arise are: what is smart and what is not smart? How does smartness happen? How is it experienced? And how smart is one entity compared to another? A framework for understanding and evaluating smartness has become essential for developing, managing, and progressing the smartness quality in critical systems.

3.3 Literature review

3.3.1 Overview

Smartness associated with consumer goods such as smartphones and 'smart' products, have recently permeated everyday life. But the smart entity concept existed much earlier. Salton (1971) described a 'smart' system of document retrieval. The smartness claim was based on its use of language analysis and a method for algorithmic optimization that compares the outcomes of multiple intermediate methods to achieve superior outcomes compared to previous systems. This section reviews smart systems from the literature.

While the term *'smart'* has not been used extensively in the literature to describe systems, some related terms do exist. These include *intelligent systems* which mimic aspects of reasoning exhibited in nature to solve different problems (Grosan & Abraham, 2011; Rudas & Fodor, 2008). Another concept is *adaptive systems* which use responsiveness to variations in system parameters to improve performance (Hayes-Roth, 1995; Mareels & Polderman, 1996). Additionally, *context-aware systems* utilize the understanding of location and situations to improve information and service relevance (Hong et al., 2009). Further, *autonomous systems* seek to improve accuracy and efficiency by eliminating human interference in system operations (Watson & Scheidt, 2005). These approaches seek to improve system outcomes relative to the classic system scenario by using intelligence.

Smartness has been attributed to systems in different domains, including agriculture, medicine, materials, public infrastructure, and industrial production. Agricultural systems include climate-smart agriculture (Jagustović et al., 2019), intelligent farming systems (Kernecker et al., 2020), adaptive irrigation systems (Canales-Ide et al., 2019), and food systems powered by IT (Nakano & Washizu, 2018). Some studies referred to climate-smart agriculture without explaining why it is considered smart (Jat et al., 2019; Long et al., 2019; Notenbaert et al., 2017). However, Jagustović et al. (2019) postulate that climate-smart agriculture (CSA) is a complex adaptive system (CAS) and has attributes such as self-organization, emergent order, and dynamic system order. Smart farming technologies (SFT) facilitate an agricultural paradigm that delivers process customization and production efficiency based on data capabilities (Kernecker et al., 2020). CSA is primarily a socio-economic system that derives its smartness from human activities. The case can thus be made that the smartness of systems is not necessarily a function of technology but rather the presence of key attributes and functionalities.

A class of drug delivery systems (DDS) in medicine is considered smart. DDS are mechanisms for transporting pharmaceutical compounds in humans or animals to achieve desired therapeutic effects (Tiwari et al., 2012). It also aims to improve the pharmacological properties of conventional or *free* drugs (Allen & Cullis, 2004). Smart DDS aims to improve outcomes by controlling the quantity, location, and timing of drug release (Gonzalez-Valdivieso et al., 2019; Zhou et al., 2019). The release trigger mechanism is based on stimuli responsiveness functionalities that sense pH levels (Samimi-Gharaie et al., 2018), enzymes, hypoxia, light, and magnetic fields (Zhou et al., 2019).

In materials, engineered living materials (ELM) that use engineered living cells for material synthesis have been labelled smart (Nguyen et al., 2018). Graphene-based materials with stimuli-responsiveness properties have also been called smart (Yu et al., 2017). Smart materials can exhibit characteristics like awareness and self-healing. Their attributes make them useful in sensor technologies, including wearable devices for monitoring applications (Yu et al., 2017).

Similarly, Industry 4.0 claims to transform industrial production into a smart state (Ramanathan & Samaranayake, 2021; Schuh et al., 2017), creating smart factories, smart supply chains, and smart products (Abdi, 2018; Nunes et al., 2017; Radziwon et al., 2014; Saad et al., 2021). Smart production systems use value chain integration to develop information transparency – ubiquitous access to quality and context-sensitive information on all production elements across the value chain. It develops autonomy and flexibility, enabling performance improvement through product innovation (Puriwat & Hoonsopon, 2021; Waris et al., 2017), mass product customization (Zawadzki & Żywicki, 2016), resource utilization efficiency (Oztemel & Gursev, 2020; Zhou et al., 2015), and better handling of uncertainty (Dequeant et al., 2016).

Industry 4.0 concepts have also been extended to cities and public infrastructure with smart cities (Habibzadeh et al., 2018), waste management (Rutqvist et al., 2020), car parking (Roman et al., 2018), water supply (Zhou et al., 2018), and transportation (Fernández-Isabel et al., 2020; Golub et al., 2019).

3.3.2 Smart system characteristics

The following sections review some important characteristics of smart systems in academic literature.

3.3.2.1 Optimization

Systems described as smart are often focused on outcome optimization. For example, smart agriculture optimizes socio-economic outcomes, including sustainability and food security (Jagustović et al., 2019; Lipper et al., 2014), yields, production efficiency, and resource utilization (Kernecker et al., 2020; Sambo et al., 2019). Smart industrial production seeks to optimize multiple production parameters, including productivity (Fragapane et al., 2020), employee wellbeing (Bordel et al., 2022), sustainability (Ghobakhloo, 2020), and product and business model innovation (Ibarra et al., 2018; Waris et al., 2017). Smart drug delivery systems target optimizing patient health outcomes by improving the therapeutic efficiency of drugs while minimizing potential harm to patients (Gonzalez-Valdivieso et al., 2019; Zhou et al., 2019). Street lighting is essential in cities (Pasolini et al., 2019). It is also a significant driver of cost and pollution. Smart street lighting provides appropriate lighting levels for every situation. It optimizes service delivery and power utilization through sensors for determining user presence and atmospheric conditions and actuating a dimming or switching functionality. According to Naqvi et al. (2020), smart cities optimize services to residents, including reducing disease burden, improving life-saving technological assistance and emergency response, and reducing resource consumption through pervasive interconnectivity that facilitates data-driven decisions.

Smart systems seek to use data capabilities and stimuli responsiveness functionalities to achieve measured, optimal actions, like the location and quantity of drug delivery in smart DDS (Samimi-Gharaie et al., 2018; Zhou et al., 2019), or quantity, timing, and location of nutrient or water delivery in smart agriculture systems (Canales-Ide et al., 2019; Kernecker et al., 2020).

3.3.2.2 Stimuli-responsiveness

Smart systems have functionality for environmental interaction. They can sense – collect data from their environment, and respond to their environment based on the collected data (Miah et al., 2019). *Smart* agricultural systems use sensors for real-time monitoring of nutrients and physical conditions around crops, and they can also actuate, releasing the required nutrients based on such monitoring (Sambo et al., 2019). The smart DDS possesses the capacity to sense and respond. They respond to stimuli such as pH level (Samimi-Gharaie et al., 2018), enzymes, hypoxia, light, and magnetic fields (Zhou et al., 2019). Stimuli-responsiveness is critical for data acquisition and autonomy (Sassone et al., 2016), which are important mechanisms through which smart systems develop intelligence and optimize outcomes.

3.3.2.3 Intelligence

The intelligence of engineered systems is related to their possession of knowledge, and it has been suggested that such systems can be referred to as ‘knowledgeable’ or ‘informed’ (Stephanopoulos & Han, 1996). Fernández-Montes et al. (2014) described a smart environment as one that acquires knowledge about its inhabitants to improve their experience. *Smart* systems generally acquire knowledge and utilize their intelligence to optimize outcomes. *Smart* transportation systems, including roads, and vehicles, utilize knowledge of traffic, passengers, environmental conditions, and incidents to optimize transportation outcomes, including safety and throughput (Toh et al., 2020). *Smart* production systems acquire knowledge on production parameters like demand, disruptions, and workers through sensing and data capabilities and optimize productivity (Rüßmann et al., 2015), safety (Adriaensen et al., 2019; Sjödin et al., 2018a), and customer satisfaction (Borangiu et al., 2019).

3.3.2.4 Flexibility

Flexibility is the ability of systems to change through learning to improve their performance. It has been called changeability, adaptability, agility, or evolution. Flexibility is essential for smart manufacturing systems (Sajjad et al., 2021). It enables reconfigurability based on learned characteristics, facilitating the capacity to handle uncertainty and variability along the value chain (Čater et al., 2021; Pansare et al., 2021). Smart transportation systems can use adaptability to improve safety and throughput by altering infrastructure parameters, including intersection configurations, road configurations, and customer messaging in response to determined or predicted traffic or environmental conditions (Toh et al., 2020).

Evolution is a peculiar context of adaptability. A perspective on evolution (Leibnitz's) is optimizing a system through generational changes (Hall & Strickberger, 2008). Evolution in engineered systems is a borrowed concept from biology, having been observed initially in nature. It is a meta functionality that optimizes other functionalities through an iterative process. For example, in the Industry 4.0 context, this iterative process is through a feedback loop between products in operation and the product development process. It is an iterative optimization method for continuous improvement and continuity, optimizing functionality and performance (Bosch & Olsson, 2016; Salkin et al., 2018).

3.3.2.5 Autonomy

Autonomy implies functioning without human inputs and is often associated with smart systems. Self-organization, emergent order, and dynamic system order are attributes of climate-smart agriculture (Jagustović et al., 2019). Smart materials can also self-organize (Nguyen et al., 2018) and self-heal (Newnham & Ruschau, 1991), and smart supply chains can self-coordinate and react autonomously to disruptions (Wu et al., 2016). Smart mobility and transportation systems rely on autonomous functionalities to optimize outcomes such as safety and throughput (Fernández-Isabel et al., 2020; Golub et al., 2019). Autonomy eliminates or reduces human fallibility, including accuracy, flexibility, speed, and cost. Autonomous vehicles are expected to save 9,600 lives annually and $50 billion in economic costs at 50% penetration (Gopalswamy & Rathinam, 2018).

3.3.2.6 Context-awareness

Context-awareness relates to a system's recognition of self and the situations in which they exist and operate (Gellersen et al., 2002). *"A system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task"* (Dey, 2001, p. 2). Smart buildings model real-time consumption requirements for lighting by creating an awareness of human environmental activities (Degha et al., 2019). Context-awareness in autonomous vehicles, smart roads, and crowd management systems has been identified as helpful in improving smart city outcomes. It improves navigation and understanding of crowd flow and city dynamics (Boukerche & Coutinho, 2019). Context awareness is also foundational for autonomous functionalities, including self-configuration, self-healing, self-optimization, and self-protection in smart power grids (Donohoe et al., 2015). Environmental context sensitivity is key to exploiting consumer smart products' capacity to satisfy user needs; context-awareness is, therefore, key to designing Smart-Product Service Systems (Carrera-Rivera et al., 2022).

3.3.2.7 Resource utilization

Zhao et al. (2019) present a smart system resource utilization narrative. The acetone-butanol-ethanol (ABE) fermentation process is labelled 'smart.' It is expected to play an important role in sustainable energy supply (Ellabban et al., 2014). The production of biobutanol through the ABE fermentation process declined over the years due to the relative cost inefficiency of the process compared to production through chemical synthesis. The recent rise in the global considerations for industrial processes' environmental impacts has shifted focus to the fermentation process. Smart ABE fermentation uses designed biomasses to improve the utilization of substrates. It utilizes resources more optimally with a resultant gain in environmental impact. Similarly, smart irrigation systems and smart manufacturing systems optimize resource utilization, including water, energy, material, and environmental impact, through optimal decision-making and autonomous actuation (García et al., 2020; Ghobakhloo, 2020).

The advent of Industry 4.0 has increased references to smart systems. Its wider interpretation of applications such as smart cities and smart healthcare beyond industrial production has also further increased the relevance of smartness as a characterization of systems. Smart systems aim to optimize outcomes. A literature review does not produce a concise framework for qualifying smart systems; however, key functionalities like stimuli responsiveness, intelligence, autonomy, and adaptability are common. Developing smartness in engineered systems would benefit from the ability to identify and measure it. This study aims to develop a framework for qualifying and classifying smartness to aid its development in engineered systems. Table 3-1 below summarises smart system characteristics in recent literature.

Study2	Autonomy	Context awareness	Flexibility	Intelligence	Optimization	Resource utilization	Stimuli responsiveness
Adriaensen et al. (2019)	x			x			x

Borangiu et al. (2019)	x			x			
Bordel et al. (2022)					x	x	x
Bosch & Olsson (2016)	x		x				
Boukerche & Coutinho (2019)	x	x		x			
Canales-Ide et al. (2019)					x	x	
Carrera-Rivera et al. (2022)		x		x			x
Čater et al. (2021)			x				
Degha et al. (2019)	x	x			x	x	
Dey (2001)		x					
Donohoe et al. (2015)		x					x
Ellabban et al. (2014)			x			x	
Fernández-Isabel et al. (2020)	x				x		
Fernández-Montes et al. (2014)		x		x			x
Fragapane et al. (2020)	x		x	x	x		x
García et al. (2020)					x	x	
Gellersen et al. (2002)		x					x
Ghobakhloo (2020)					x	x	
Golub et al. (2019)	x						
Gonzalez-Valdivieso et al. (2019)	x			x	x		x
Gopalswamy & Rathinam (2018)	x	x		x			x
Ibarra et al. (2018)					x		
Jagustović et al. (2019)	x				x	x	
Kernecker et al. (2020)	x				x		x
Lipper et al. (2014)	x				x		
Miah et al. (2019)							x
Naqvi et al. (2020)	x				x		x
Newnham & Ruschau (1991)	x						
Nguyen et al. (2018)	x		x				x
Pansare et al. (2021)			x				
Pasolini et al. (2019)					x	x	x
Rüßmann et al. (2015)				x	x		x
Sajjad et al. (2021)	x		x	x	x		
Salkin et al. (2018)	x		x	x			
Sambo et al. (2019)					x		x
Samimi-Gharaie et al. (2018)	x		x		x		x
Sassone et al. (2016)	x	x					x
Sjödin et al. (2018)	x			x			x
Toh et al. (2020)			x	x			
Waris et al. (2017)	x		x	x	x		x
Wu et al. (2016)	x			x			x
Zhao et al. (2019)	x	x			x	x	
Zhou et al. (2019)				x	x		x

Table 3-1 - Smart systems characteristics in literature

3.3.3 Systems theory

Systems are composed of components that work collectively to perform functions (Teece, 2018. Systems theory posits that such a system is more than the sum of its parts i.e., it is able to deliver value, not realizable through the individual functioning of its components, and the health or quality of systems is better explained by their holistic functioning rather than isolated considerations of its parts (reductionism) (Bar-Yam, 2018; Simon, 1991). Furthermore, system performance is a function of congruence, the quality of alignment amongst the system elements (Nadler & Tushman, 1980), alluding to the value of system's design which translates complexity to outcomes.

This study develops a conceptual framework for smart systems. Conceptual frameworks are useful for organizing complex entities and communicating their structure (Bordage, 2009; Miles & Huberman, 1994). The framework developed facilitates the translation of the complexity of smart systems into design, enabling understanding and implementation of the systems.

3.4 Method

The study aims to develop a conceptual framework for smart systems that answers '***what***' a smart system looks like and '***how***' smartness is developed. The answers to the questions will help us identify smart systems and evaluate the smartness of an entity. This study uses qualitative research (Edmondson & McManus, 2007) to develop a process description and a functional specification for smart systems. To achieve its objectives, the study aimed to explore existential phenomenology, the research approach that explores experts' lived experiences in a field for theory derivation (Collingridge & Gantt, 2008; Wang, 2022).The method consists of semi-structured interviews with experts and analysis of the responses, which are suitable for developing new theories as there is little prior understanding of relationships and factors in the area (Nowell & Albrecht, 2018).

All the interviews are recorded, transcribed, and coded using the Gioia methodology (Gioia et al., 2013). The methodology derives the first-order themes through open coding (Strauss & Corbin, 1998). These capture the respondents' thoughts as verbatim as possible. The second-order concepts are derived by applying the researcher's conceptual perspectives on the first-order concepts, identifying underlying trends emerging as themes. The researcher further analyses the second-order concepts, applying the appropriate theoretical frameworks, in this instance, systems theory, to facilitate the emergence of aggregate dimensions.

The interview guide is referenced in Appendix A. The participants were asked for their definition of smartness in a system context, and further questioning required them to provide necessary clarifications. All the interviews were recorded and transcribed. The responses were coded using the Gioia methodology (Gioia et al., 2013). The first-order themes, second-order concepts, and aggregate dimensions were determined and coded to facilitate analysis.

3.4.1 Participant Selection

A key assumption of the Gioia methodology is that the research participants are knowledgeable agents (Gioia et al., 2013). The study's participants' selection was crucial to theory development and achieving accurate, reliable, and generalizable insights as the methodology has excelled in situations where participants have knowledgeable experiences (Gehman et al., 2017). The study targeted personnel of large global firms providing technology services associated with the identified smart systems characteristics. The targeted firms all reported revenues greater than USD 30B in 2021. As the study relies on participants' lived experiences, only those with twenty years of experience or more were targeted. Key personnel of these firms are identified in whitepapers produced for marketing purposes, these were approached, and snowballing sampling technique was deployed thereafter (Etikan et al., 2016), with respondents helping to enlist their colleagues as respondents. Sixteen interviews were conducted, as convergence was achieved, with no new themes or concepts emerging. Collectively, the work experience of research participants spanned many countries. At the time of the interviews, they were based in Australia, France, the USA, and Malaysia but spanned many more countries across their careers. All respondents were senior leaders of technology functions within major global companies at the time of the interviews. They were also associated with Industry 4.0 and digital transformation projects and functions. The interviews were conducted in English between September and December 2020. Industry 4.0 and Technology leaders at these firms were targeted because of the extensive transformation project experience they have between them. The study employed measures to ensure the validity of the research, including initial expert validation (Straub, 1989) in the interview guide construction and triangulation (Kitto et al., 2008) in the data collection and analysis process. The diversity of industry expertise also makes them technology agnostic and broadens their scope and views. Appendix E – Participant profiles, provides a summary of the Respondents.

Flinders University Human Research Ethics Committee reviewed and approved this study's ethical aspects.

3.5 Results

Respondents provided useful insights that can be used to progress the conceptualization of smartness. Table 3-1 shows the participants' responses to the question "what is smartness?" The first-order concepts cover the critical deductions and concepts captured in the initial and follow-up questions.

Respondent	Smartness description	First-order concepts
1	Ability to collect data for the purpose of generating autonomous functionalities and more accurate actuation by learning from the data	Data, autonomy, accuracy, system function, learning, actuation, sensing
2	The capacity to solve problems using the most current and relevant information	Data, information, optimization, actuation, quality, intelligence, problem-solving

3	Ability to operate autonomously, learn, evolve and develop awareness	Autonomy, awareness, learning, evolution, action, function, adaptability
4	The use of data to achieve superior outcomes	Data, quality, actuation
5	The use of intelligence, natural or artificial, to achieve new capabilities	Intelligence, capability, action
6	The ability to use sensors to collect data over connected infrastructure and application of AI to facilitate rapid decision making	Data collection, data processing, intelligence, speed, decision-making, sensing, connectivity, enablement, network, communication
7	The use of data and intelligence to introduce precision into achievable socioeconomic outcomes	Data, intelligence, system function, optimization, accuracy, forecasting
8	The use of information and intelligence to achieve sustainable outcomes	Information, data, intelligence, resource utilization, optimization
9	Utilising embedded intelligence or developing updated intelligence for consistently making optimal decision	Optimization, decision-making, efficiency, uncertainty, transparency, accuracy, consistency
10	Ability to sense and respond and self-correct	Sensing, self-correction, action, autonomy
11	Use of stimuli responsiveness and adaptive control to act intelligently	Stimuli-responsiveness, environmental interaction, adaptive control, actuation, intelligence, flexibility, agility
12	Acting with intelligence, static or dynamic.	Intelligence, actuation, system function
13	Using data to optimize outcomes	Data, optimization, actuation
14	Effective utilization of resources to achieve better outcomes	Effectiveness, optimization
15	Ability to learn, change, and improve while functioning	Learning, intelligence, action, system function, adaptability, flexibility, agility
16	Ability to evolve, developing the functionalities required for optimal operations	System function, evolution, optimization

Table 3-2 - Participant's responses

Aggregate dimensions	Second-order concepts	First-order concepts	Respondent #
Stimuli-responsiveness	Actuation	action	3,5,10,15
		actuation	1,2,4,11,12,13
		capability	5
		enablement	6
		problem-solving	2
		system function	1,3,7,12,15,16
	Data acquisition	Data	1,2,4,7,8,13
		Data collection	6
		Environmental interaction	11
		Sensing	1,6,10
	Stimuli-responsiveness	Stimuli-responsiveness	11
Intelligence	Data capability	communication	6
		connectivity	6
		data processing	6

		information	2,8
		network	6
		transparency	9
	Decision	decision-making	6,9
	Intelligence	forecasting	7
		intelligence	2,5,6,7,8,11,12,15
		uncertainty	9
	Knowledge	learning	1,3,15
Functionality	Autonomy	adaptive control	11
		autonomy	1,3,10
		self-correction	10
	Flexibility	adaptability	3,15
		agility	11,15
		awareness	3
		evolution	3,16
		flexibility	11,15
Optimization	Optimization	accuracy	1,7,9
		consistency	9
		Effectiveness	14
		efficiency	9
		optimization	2,7,8,9,13,14,16
		quality	2,4
		resource utilization	8
		speed	6

Table 3-3 - Analysis of responses

3.5.1 Smart systems dimensions

The summary of the Gioia methodology process's outcome is the synthesis of the first-order concepts into second-order concepts and aggregate dimensions presented in Table 3-2. The results exposed four aspects of smartness – ***stimuli-responsiveness***, ***intelligence***, ***functionality***, and ***optimization***. The three dimensions are pervasive concepts for smartness and collectively define the underlying process for smartness.

3.5.1.1 Stimuli-responsiveness

Eleven respondents directly connected smartness and stimuli responsiveness. The exceptions are Respondents 5, 9, 14, 15, and 16, whose thinking focused on the smartness process's functional outcomes. Respondent 11 defined smartness as the *"use of stimuli responsiveness and adaptive control to act intelligently."* The respondents envisioned that smartness starts with a system's ability to elicit useful data from its operating environment through sensing and concludes with its response to the data collected. Respondents 1, 6, and 10 highlights the acquisition of data through sensing, the described smartness respectively as:

> *"Ability to collect data for the purpose of generating autonomous functionalities and more accurate actuation by learning from the data." (Respondent 1)*
>
> *"The ability to use sensors to collect data over connected infrastructure and application of AI to facilitate rapid decision making." (Respondent 6)*
>
> *"Ability to sense and respond and self-correct." (Respondent 10)*

Systems acquire data from their operating environment through sensing and respond to their environment through actuation. The stimuli responsiveness cycle is completed through actuation. Respondents identified that smart systems respond to stimuli autonomously. Respondent 1, quoted above, referenced accurate actuation in describing smartness, and Respondent 10 described smartness as involving response to the stimulus and self-correction. All respondents associate smartness with some action, including decision-making (Respondents 6 and 9), resource utilization (Respondent 14), system functioning (Respondents 12 and 16), and problem-solving (Respondent 2).

3.5.1.2 Intelligence

The respondents agree that smart systems act intelligently. Eleven respondents directly referenced intelligence, learning, knowledge, or decision-making. A further respondent referenced autonomy which has a direct dependence on intelligence. Respondent 12 described smartness as *"acting with intelligence,"* and Respondent 11 described it as using *"stimuli responsiveness and adaptive control to act intelligently."* Respondents propose that smart systems are defined by their ability to use intelligence. Respondents 2, 6, 7, 8 and 9 identified data as a key component of building intelligence. Respondent 7 described smartness as using *"data and intelligence to introduce precision into outcomes."*

Aspects of intelligence identified include learning and improving (Respondent 15), decision-making (Respondents 6 and 9), handling uncertainty (Respondent 9) and problem-solving (Respondent 2).

3.5.1.3 Functionality

Smart systems exhibit functionalities by which they optimize outcomes. Respondent 16 described smartness as the following:

> *Ability to evolve, developing the functionalities required for optimal operations*

The study identified two Important functionalities, autonomy and flexibility.

3.5.1.3.1 Autonomy

Respondents 1, 3, 10, and 11 identified the autonomous functionalities of smartness for optimizing outcomes. Respondents 3 and 10 described autonomy as key to smartness. According to them, smartness is:

> *Ability to operate autonomously, learn, evolve and develop awareness (Respondent3)*
>
> *Ability to sense and respond and self-correct (Respondent 10)*

Respondents 1 and 11 provided insights into the role of autonomy. According to Respondent 1, smart systems optimize actuation through autonomous functionalities. They described smartness as the:

> *Ability to collect data for the purpose of generating autonomous functionalities and more accurate actuation by learning from the data.*

Respondent 11 associated it with intelligence, describing smartness as the:

> *Use of stimuli responsiveness and adaptive control to act intelligently*

Autonomy is thus a function of smart systems for optimizing system actions.

3.5.1.3.2 Flexibility

Smart systems are flexible through features like adaptability, evolution, and context awareness. Respondents 3 and 16 identified evolution as a characteristic of smartness. Respondent 16 identified the purpose of evolution as improving capacity for optimization through new or improved functionalities. Similarly, Respondent 15 associated it with flexibility improvement. They described smartness as:

Ability to learn, change, and improve while functioning

Respondent 11 associated flexibility with intelligence through adaptive control, describing smartness as the *"use of stimuli responsiveness and adaptive control to act intelligently."*

Through flexibility, smart systems improve existing functionalities for optimizing outcomes. They can also develop new optimization functionalities through evolution.

3.5.1.4 Optimization

The quality of smartness is experienced through its functional optimization. According to respondents, smart systems optimize outcomes, including actuation accuracy (Respondent 1), development of new capabilities (Respondent 5), precision of outcomes (Respondent 7), optimality and consistency of decision quality (Respondents 9 and 13), and outcome sustainability (Respondent 8).

Respondent 13 summarized the optimization function of smartness by describing it as *"using data to optimize outcomes."*

3.5.2 Classification

The study identified intelligence as critical for smart systems. The study identified that smart systems ***use*** intelligence (Respondents 5, 8, and 12) and, in other instances, ***develop*** intelligence (Respondents 9 and 12), thus referencing different classes of smart systems. The mode of intelligence application is thus important for classifying smart systems. We identified two modes of intelligence in smart systems. The first mode involves intelligence that is acquired only at system design and is thus hard-coded into the system. Such intelligence is final and unaffected by the system's operation, including data acquisition. We refer to this mode as static intelligence, as the system does not learn from data. The second mode refers to intelligence achieved through analysing the data acquired in the system's operations. The body of intelligence, in this case, is dynamic, changing with data acquisition. We conceive the base class of systems as one without intelligence; such a system will be

non-smart as smart systems act with intelligence (Respondent 12). The system that uses embedded, static, or hard-coded intelligence are identified as ***semi-smart.*** In contrast, those that develop intelligence utilize data to create dynamic intelligence, conceptualized as ***fully smart*** systems. Smart systems exhibit stimuli responsiveness, intelligence, functionality, and optimization characteristics. Any system missing at least one of those characteristics would be non-smart.

Table 3-3 summarises the classification of smart systems.

System	**Stimuli-responsiveness**	**Intelligence**	**Functionality**	**Optimization**
Non-smart	One or more dimensions not represented			
Semi-smart	Present	Static Intelligence	Present	Present
Fully-smart	Present	Dynamic Intelligence	Present	Present

Table 3-4 - Smart system classification

Figure 3-1 is an illustration of the smart system model from this study. The dashed line connecting *data* and *knowledge* represents learning and distinguishes fully-smart systems from semi-smart systems.

3.5.3 The smart system framework

Smartness is characterized by stimuli responsiveness. According to Respondents 1, 6, and 10, smart systems acquire data from their environments through sensing. Respondent 11 further notes that they use data to generate intelligence, clarifying the distinctions between smart systems, Respondents 9 and 12 identified that some systems learn while others have static (hard-coded) intelligence. Respondent 16 concluded that smart systems ultimately function optimally and noted that there are functionalities necessary for optimization. Respondents 3, 10, and 15 recognized autonomy and flexibility as key functionalities for system optimization. Figure 3-1 represents the model for smart systems emergent from the study. From a systems theory perspective, the model presents the functional view of smart systems, depicting how components collectively achieve the holistic objective of the system to optimize outcomes.

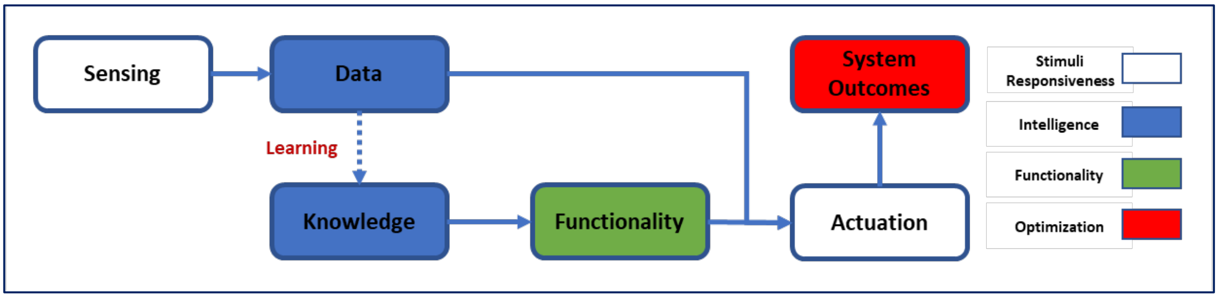

Figure 3-1 - Smart system

3.6 Discussion

The study characterized smartness as the application of intelligence for a system's functional optimization, identifying four key concepts that define smartness: responsiveness, intelligence, optimization, and system functionalities. The study also classified smart systems based on their mode of applied intelligence. Smartness hinges on the application of intelligence (Habibzadeh et al., 2018; Zhao et al., 2018). From Table 3-3, the mode of intelligence is the key parameter for classifying smart systems. While the framework does not quantify system intelligence, the dynamism is material. Non-smart systems are the generic systems that translate inputs into outputs without recourse to intelligence. They are not the focus of this research.

The difference between semi-smart and fully smart systems relates to the amount of uncertainty they can address. Semi-smart systems address scenarios where the variations are understood and addressed at systems design through hard-coded intelligence. In contrast, fully smart systems can deal with environmental changes not contemplated at system design. Smart drug delivery systems (DDS) are an example of semi-smart systems. The intelligence is hard coded and unaffected by data. Learning would be useful in the context of cancer spreading or disease pathogens morphing into forms not considered at system design. This inability to learn is a potential for improvement as smart DDS evolves. Conversely, Industry 4.0 is required to deliver responsiveness to variability in its operating environment in ways that are often not predictable at system design, like factories being able to produce future designs that are yet unknown or being responsive to disruptions in the supply chain that are impossible to predict. Several of these aspects require fully smart systems. Smart cities and smart transportation systems are also Industry 4.0 contexts where fully smart system applications are common. This is because of the role of human agents as system factors with a high degree of unpredictability.

Stimuli-responsiveness was found to be pervasive for smartness. Most interview respondents made the connections between stimuli responsiveness and smartness. Stimuli responsiveness in engineered systems is implemented using sensors and actuators, the twin functions which implement the infrastructure for stimuli-responsiveness (Zhao et al., 2018). The smart systems model (Figure 3-1) illustrates the importance of stimuli responsiveness, putting it at the start (data acquisition) and the end (optimization by autonomous actuation) of the smartness process. This can be understood in the context of the role of intelligence in smartness. Research respondents variously defined smartness as having intelligence as the basis for action. The smart system is thus concerned with generating and using intelligence. According to Botha (2019), intelligent processes build on acquiring vast amounts of data through which they learn, adapt, and optimize. Sensing functionality is critical for the currency of data, as the system captures real-time data from its environment. The system derives intelligence from the data to generate and drive actuation, the system's mechanism for optimized actions. Respondent 2 established that the currency of information is necessary for smartness. This logic resonates with studies that have established a strong link between smartness and instrumentation (Bibri, 2019; Harmon et al., 2015; Harrison & Donnelly, 2011). Sensing and actuation are functionalities of instrumentation. Through sensing, systems collect essential data related to their operations from their environment, and through actuation, a system responds with action.

Given that smart systems, operations translate to sequences of data acquisition, intelligence generation and intelligence application through autonomous functionalities, enhancing data capabilities is core to smartness development. Table 3-2 shows that data capability and data processing infrastructure are crucial for smart systems by contributing to intelligence and stimuli responsiveness. Data capability refers to the system's capacity for acquiring, managing, and exploiting data to create value for the system. Respondent 2 links the smart system functioning with information quality (currency and relevance). Data capability enables information quality, facilitating the development of smart system functionality, including autonomy, flexibility, and decision-making.

There is a tendency to characterize smart systems as simply better systems than their legacy, non-smart counterparts (Alter, 2019; Corsini et al., 2019; Habibzadeh et al., 2018). This tendency is attributable to the optimization characteristic of smart systems. The study established that smart systems optimize outcomes. Examples of optimization by smart systems include smart farming systems optimizing water usage, land usage, and crop yields (Jagustović et al., 2019; Kernecker et al., 2020). Smart transportation systems optimize infrastructure efficiency, throughputs, and resource consumption (Habibzadeh et al., 2018; Huo et al., 2019; Roman et al., 2018), and smart factories optimize productivity and resource utilization (Chen et al., 2018). The functionalities exhibited by smart systems enable the system to optimize important outcome parameters. A smart waste management system utilizes its predictive capability to optimize logistics (Rutqvist et al., 2020), and smart factories use autonomy and flexibility to optimize decision-making and resource efficiency (Lichtblau et al., 2015).

3.7 Conclusion

Smartness is the application of intelligence in the operations of a system. Data, stimuli responsiveness, intelligence, and optimization are base characteristics of smartness. Smart systems seek to take the best quality action possible based on the best decision. They acquire data from their environment to synthesize knowledge and feed the decision process. Data quality, the currency of intelligence, and effectiveness of actuation are thus quality parameters of smartness.

We identified three classes of systems concerning smartness: non-smart systems, semi-smart systems, and fully-smart systems. Non-smart systems do not have the full complement of stimuli-responsiveness, intelligence, functionality, and optimization. Semi-smart systems are capable of sensing and actuating. Sensing provides data for decision-making based on hard-coded intelligence; they do not develop further intelligence through their operation. Fully-smart systems generate intelligence from data acquired through sensing and utilize their intelligence in system operations. Thus, intelligence is not hard-coded but dynamic. Furthermore, systems could develop awareness, adapt to changes in their environment and operational requirements, evolve desired features and functionalities, predict future values of relevant variables, and function autonomously.

The advent of Industry 4.0 drives the appetite to implement smart technologies and build smart production organizations. The development of smart capabilities in production organizations, including in factories, products, and supply chains, is a transformation process that lends itself to a road-mapping approach (Schimpf & Abele, 2019). This study distils smartness into functional components around which transformation can be designed. Hence, it is a management tool for transformation planning. Overall, it provides improved clarity in the conceptualization of smartness, which paves a strong foundation for future empirical research.

3.7.1 Practical implications

There are two main implications of this study. The first is the identification and classification of smart systems. The framework presented in Table 3-4 provides a basis for smart system identification and classification. System identification uses statistical methods to develop mathematical models for implementing and optimizing systems (Ljung, 2010). The framework developed in this study identifies useful parameters for input and output data consideration in an identification exercise for smart systems. This thus provides a basis for further developments in the evolution of smart systems. Secondly, the smart system dimensions identified in this study facilitate the maturity modelling of smartness as a capability. Maturity models are an effective capability measurement tool. Their application, however, relies on measuring the target capability's appropriate dimensions. This study identifies the dimensions of smartness, thus enabling the application of maturity modelling for measuring smartness as a capability. This is potentially crucial for Industry 4.0, where smartness is the capability developed through digital transformation for production performance improvement.

3.7.2 Future directions and research limitations

The identification of semi-smart and fully-smart classes of smart systems highlights the importance of the impact of the scope of variabilities in the system operating environment on system design and functionality. Further research on modelling the relationships between a smart system and its operating environment to characterize the possible variabilities is an interesting and useful potential research subject.

This study is based on the lived experiences of the research participants. The set of participants thus represents limitations to the research.

4 DRIVING SMARTNESS FOR ORGANIZATIONAL PERFORMANCE THROUGH INDUSTRY 4.0: A SYSTEMS PERSPECTIVE

Journal publication: *This chapter was accepted for publication in the Journal of Manufacturing Technology Management: Abiodun, T., Rampersad, G.C. and Brinkworth, R. (2023): "Driving smartness for organizational performance through Industry 4.0: A systems perspective: DOI (10.1108/JMTM-09-2022-0335)" The Student's Contribution was the majority of the publication (95%), specifically research design, data collection and analysis, and writing. The supervisors had a guiding, reviewing, and editing role (5%).*

4.1 Abstract

Purpose: The internationalization of business has grown the production value chains and created performance challenges for industrial production. Industry 4.0, the digital transformation of industrial processes, promises to deliver performance improvements through smart functionalities. This study investigates how digital transformation translates to performance gain by adopting a systems perspective to drive smartness.

Design/methodology/approach: This study uses qualitative research to collect data on the lived experiences of digital transformation practitioners for theory development. It uses semi-structured interviews with industry experts and applies the Gioia methodology for analysis.

Findings: The study determined that enterprise smartness is an organizational capability developed by digital transformation, it is a function of integration and the enabler of organizational performance gains in the Industry 4.0 context. The study determined that performance gains are experienced in productivity, sustainability, safety, and customer experience, which represents performance metrics for Industry 4.0.

Originality: Existing studies recognized the positive impact of technology on performance in industrial production. The study addresses a missing link in the Industry 4.0 value creation process. It adopts a systems perspective to establish the role of smartness in translating technology use to performance outcomes. Smart capabilities have been the critical missing link in the literature on harnessing digital transformation in organizations. The study advances theory development by contributing an Industry 4.0 value model that establishes a link between digital technologies, smartness, and organizational performance.

Research implications: This study contributes a model that inserts smartness in the linkage between digital transformation and organizational outcomes to the digital transformation and production management literature.

Keywords: digital transformation, Industry 4.0, organizational performance

4.2 Introduction

Production value chains have grown significantly as international business and globalization progress. This increased size and scope of production value chains have created a challenge for their performance. Performance considerations include concerns for production's social and environmental implications (Furstenau et al., 2020), variability in the production environment (Dequeant et al., 2016), the need for more resilience in supply chains (Ralston & Blackhurst, 2020), and the growing demand for custom products to meet unique needs of more diverse customers (Aheleroff et al., 2019; Tseng & Jiao, 1997).

Resilience in times of disruption is an important consideration for production value chain performance. Some studies have suggested that global value chains are more vulnerable to disruptions (Miroudot, 2020). Socio-economic and biological contagion plays important roles in global crises, as highlighted by the COVID-19 pandemic (Hansen, 2021; Hsiang et al., 2020); thus, global value chains are both a risk and at risk. At the organizational level, variability in production parameters characterizes the expansive value chain and introduces uncertainty in production performance (Dequeant et al., 2016; Smorodinskaya et al., 2021). Industry 4.0, deploying cyber-physical systems to integrate the production value chain enables smartness in production systems to respond to this risk and optimizes the performance of production enterprises (Fragapane et al., 2020). This smartness facilitates the flexibility of production systems, products, and supply chains for addressing the variability challenge (Enrique et al., 2022; Shahin et al., 2020; Xie et al., 2020).

Industry 4.0 has emerged as important to the productive capacity of organizations in uncertain environments (Lee & Trimi, 2021). The digital transformation literature has positioned Industry 4.0 as a technology-led value creation framework and focused the Industry 4.0 discourse predominantly around technology (Oztemel, 2018; Oztemel & Gursev, 2020), with several studies establishing the contribution of technologies to production performance (Büchi et al., 2020; Dalenogare et al., 2018; Lin et al., 2019). The Industry 4.0 literature further discusses the expectation of smartness as a characteristic of transformation through which the enterprise optimizes outcomes (Adamik & Sikora-Fernandez, 2021; Chronopoulos et al., 2020; Lichtblau et al., 2015). The literature references the factory (Cheng et al., 2018), supply chain (Tripathi & Gupta, 2021), and products (Nunes et al., 2017; Salkin et al., 2018) as elements of the production value chain through which smart capabilities materialize. Smartness is thus positioned as a link between technology and value realization.

However, the nuances of the relationships between smartness, technology, and organizational performance are often overlooked, necessitating a more indepth look at the holistic systems approach. From the above, two issues come to the fore. First, the performance of a value chain is multi-dimensional and not simply characterized by its throughput. The impact of value chain activities on its multiple stakeholders must drive the notion of performance, culminating in factors such as sustainability (Baier et al., 2020). The literature remains limited in examining the impact of Industry 4.0 on broader organizational performance contexts such as customer experience, safety, and sustainability. It follows that constructing an appropriate performance metric for the production firm must include a comprehensive understanding of its stakeholders and their interests in the enterprise. Secondly, the relationships between technology, smartness, and performance highlight the role of smartness as the organizational capability emergent from end-to-end digital transformation of the production value chain, describes the Industry 4.0 value path and would benefit digital transformation strategy formulation.

Given such complexities, a systems perspective is needed to explore how inputs are converted to outcomes through smartness. Therefore, this study will improve the understanding of relationships between smartness, technology, and organizational performance, to support manufacturing managers in developing Industry 4.0 strategy and harnessing the value from Industry 4.0 interventions.

4.3 Literature review

4.3.1 Industry 4.0, systems theory, and production performance

The value proposition of Industry 4.0 has been discussed extensively in academic literature. Many studies attribute Industry 4.0's value creation potential to a direct effect of *Industry 4.0 technologies* on aspects of the value chain, establishing a causal relationship between technology and performance. This approach translates to a reductionist view of the value-creation process as it focusses on siloed treatment of specific processes. Following this approach, Dalenogare et al. (2018), Qader et al. (2022) and Szász et al. (2020) explored the impact of Industry 4.0 technologies implementation on industrial performance metrics including product, supply chain performance, cost, quality, delivery, and flexibility. Lin et al. (2019) identified drivers of Industry 4.0 strategy adoption, studying the relationship between these factors, adoption and performance (financial, innovation, stock market return, and supply chain performance) and Büchi et al. (2020) considered technology from the perspective of the attitude toward adoption and established its impact on performance. Overall, these studies identified measures of Industry 4.0 technology adoption, implementation or application in production processes and established that Industry 4.0

technologies improve performance. Another approach considers the interactions between technology and organizational factors or management practices in the value-creation process. In addition to considering the causal relationship like the first school of thought, Szász et al. (2020) also determined that firm size positively influences adoption, thus, contributing to performance. Studies also found that Industry 4.0 enhances lean and JIT practices (Buer et al., 2018; Lai et al., 2019; Rosin et al., 2020), eliminating waste and increasing productivity.

Fewer studies have considered Industry 4.0 as a systemic effect in investigating its value-creation process. Fatorachian and Kazemi (2021) and Ghadge et al. (2020) explored the impact of Industry 4.0 on the production supply chain performance using frameworks underpinned by systems theory. They examined the impact of Industry 4.0 on supply chain performance using frameworks that quantified the systemic impacts of Industry 4.0 on the production enterprise. Table 1 summarizes recent studies addressing the organizational value proposition of Industry 4.0. The measure of Industry 4.0 utility is indicative of the approach to value creation. While the studies with a holistic approach measured Industry 4.0 based on organizational capabilities created, the reductionist approach measured technology implementations and management efforts. There does not appear to be adequate research exploring the performance impact of Industry 4.0 across the entire production value chain based on a holistic approach. A systems perspective is needed to advance the Industry 4.0 stream of literature beyond the predominant focus on reductionist values in the production organization. The influence of specific technologies on performance or practices like lean and Just in Time (JIT) does not consider end-to-end integration and the role of resultant information transparency on value creation.

Systems theory posits that a system can be optimized by eliminating reductionist approaches to its operation and management (Bar-Yam, 2018; Johnson et al., 1964; Teece & Pisano, 1998). By integrating the value chain end-to-end (Bartodziej, 2017; Wang et al., 2016), Industry 4.0 appeals to systems or holistic organization of the production enterprise rather than a reductionist approach to delivering value. However, many studies seek to explain the value proposition of Industry 4.0 by showing the impact of technology on aspects of the value chain, not the holistic effects of integrating the value chain. Furthermore, many technologies that are usually referenced, like sensors, robotics, and automation, and their application in industrial production predates Industry 4.0 (Haidegger et al., 2019; Lloyd Spetz et al., 2001; Tantawi et al., 2019).

Study	Industry 4.0 Measurement	Performance Metrics
Dalenogare et al. (2018)	Adoption of Industry 4.0 technologies.	Product (innovation, customer), Operational (Cost, productivity, process efficiency), Side effects (sustainability, employee wellbeing)
Szász et al. (2020)	Adoption of Industry 4.0 technologies	Cost, quality, delivery, and flexibility
Lin et al. (2019)	Industry 4.0 strategy adoption.	Financial, innovation, stock market return, and supply chain performance
Büchi et al. (2020)	Attitude towards Industry 4.0 based on the number of Industry 4.0 technologies adopted and the extent of their embeddeness in business operations	Six factors addressing productivity, product quality, resource utilization and product innovation.
Rosin et al., 2020	Adoption of Industry 4.0 technologies (IoT, Simulation, Autonomous Robots, Augmented Reality, and Big Data and analytics)	JIT Capability level
Lai et al., 2019	Industry 4.0 technologies application	Waste reduction
Qader et al. (2022)	Technology implementation (IoT, Machine Learning, and Blockchain)	Operational and financial performance of the supply chain
Fatorachian and Kazemi (2021)	Integration and transparency	Responsiveness, flexibility, dependability, product or service quality, efficiency, and effectiveness
Ghadge et al. (2020)	Technology-enabled information transparency	Adaptability, agility, and flexibility

Table 4-1 - Industry 4.0 value creation in literature

This study applies systems theory in exploring the value creation potential of Industry 4.0 across broad performance metrics, modeling relationships between digital transformation, enterprise smartness, and production performance. Therefore, the study addresses the key research question of ‘How does Industry 4.0 drive organizational performance, and how does smartness play a critical role in this process?’

The industrial production system comprises devices, materials, systems, processes, people, and partnering organizations (Chukalov, 2017; Tabim et al., 2021). Integrating them into a single system for holistic management creates a socio-technical system consisting of technical and non-technical parts (Sony & Naik, 2020). Socio-technical systems are characterized by extensive interactions among independent heterogeneous actors, resulting in highly volatile and unpredictable operating environments. The system must thus regulate agents’ actions to optimize its function (Dalpiaz et al., 2013). Industry 4.0 approaches this optimization challenge of the production system through smartness (Lichtblau et al., 2015).

4.3.2 Smartness

Smartness is the characteristic of gaining optimization through the application of intelligence built on stimuli-responsiveness (Nguyen et al., 2018; Samimi-Gharaie et al., 2018; Zhao et al., 2018). Smartness is linked to information transparency (Abiodun et al., 2022; Wu et al., 2021). Furthermore, information transparency is a function of integration (Guo et al., 2022). It follows that the smartness potential of an enterprise or system depends on the quality of integration and is attributable to holistic approaches. The value-creation potential of digitalized industrial production systems is tied to information transparency (Flatt et al., 2016). By integrating the value chain and enabling information transparency, Industry 4.0 facilitates smartness, including the smart factory (Radziwon et al., 2014; Wang et al., 2016), the smart supply chain (Wu et al., 2016), and the smart product (Nunes et al., 2017; Salkin et al., 2018). Through real-time information on production elements, smart capabilities enhance autonomy, flexibility, decision-making, and productivity (Alani & Alloghani, 2019; Barreto et al., 2017; Cortés Serrano et al., 2018).

The smart factory is a network of devices, systems, and processes for production, implementing an automation pyramid from ground-level devices with sensing and actuation functionalities to enterprise information systems like enterprise resource planning (ERP) (Zuehlke, 2010). Smart factories have smart systems characteristics, including intelligence, awareness, and environmental interaction (Chen et al., 2018; Radziwon et al., 2014). The smart factory is underpinned by cyber-physical integration. The physical elements are instrumented with sensing and actuation, allowing them to integrate with the virtual elements and interact with their environment. The smart factory aims to engender flexibility in the production enterprise and enable agility in product development and resilience to variability in the operating environment (Bortolini et al., 2018; Chen et al., 2018).

The smart supply chain can enable flexibility of the production value chain through autonomous recovery from disruptions and optimization of logistical functions (Wu et al., 2016). The problem statement for the classic supply chain is optimizing the cost of having items at the right place and time (Mallik, 2010). Industry 4.0 uses smart system functionalities to optimize supply chain management goals. Through horizontal integration, the participating entities in a supply chain are integrated with interoperable business functions. The integration can facilitate real-time information about articles traversing through the chain, enabling autonomous logistic functionalities based on optimal decision-making (Gupta et al., 2019; Sodhi & Tang, 2019).

The smart product can automate embedding customer experience, feedback, and requirements into production. In the reverse direction, it can automate maintenance and continual improvement of products and services, creating a dynamic product lifecycle loop designed to optimize customer experience and manufacturers’ productivity (Nunes et al., 2017; Salkin et al., 2018). The smart product builds on the end-to-end engineering integration in the production value chain and sensing and actuation features on the product (Romero & Noran, 2017).

4.3.3 Industry 4.0 performance metrics

A clear value proposition is necessary to drive the vision of Industry 4.0 and digital transformation (Rupp et al., 2021). The value proposition would be informed by its implication to stakeholders for performance outcomes (Baier et al., 2020). In designing systems, there is a tendency to focus on functional relevance, leading to specifications narrowly constrained within the system's technical boundaries and insufficient consideration for its wider implications (Coakes & Elliman, 2002). This narrow view of systems design translates to a constraint on its ability to fulfill its purpose. Similarly, a holistic view of business performance requires an understanding of its implication for its stakeholders – those it impacts and those that impact it (Parmar et al., 2010). The organizational performance context thus encompasses notions of sustainability and factors aligned to the interests of other stakeholders, in addition to the financial success of the enterprise (Baier et al., 2020; Harrison & Wicks, 2013; Laplume et al., 2008). Determining performance objectives is therefore linked to identifying stakeholders.

The pattern of Industry 4.0's emergence provides some insight into its stakeholders and performance considerations. Specific concurrent shifts in the global socio-economic landscape were very influential in its development and raised the significance of stakeholders, beyond shareholders, to the production enterprise (Lasi et al., 2014). Its key characteristics, including, mass product customization, optimization of resource use, reduction of environmental impact, and flexibility of production systems (BMBF, 2014; Ghobakhloo, 2020; Jiao et al., 2021; Prause, 2015; Tripathi et al., 2021) address the interests of these stakeholders.

Connections have been made between globalization, global governance, and digital technologies (Voronkova et al., 2020). The value proposition of digitally integrating the value chain is increased as it grew in scope due to globalization and the internationalization of business. These transnational value chains have some challenges, including sustainability due to increasing socio-economic impact on the environment and people not involved in the business (Prause, 2015; Zhu et al., 2018) and new operational challenges to productivity due to size and complexity (Strange & Zucchella, 2017). Variability is challenging for production, and the increased complexity of value chains introduces more variability to the supply chain and production processes (Núñez-Merino et al., 2020). Furthermore, small and medium enterprises (SMEs) are part of complex supply chains. Their success increasingly requires functional and process integration within the supply chain networks based on digital technologies (Türkeș et al., 2019).

A regime of customer influence is also emerging from changing customer behavior (Jiang et al., 2006). The Henry Ford notion of customers adjusting their tastes to the product is no longer feasible; products must be flexible and fit with the customer (Lasi et al., 2014). The demands of this change are beyond new products. A paradigm shift to customer-centric production is necessary (Guo et al., 2020).

The increasing scope of the production value chain creates challenges for production performance. Industry 4.0 seeks to respond to these challenges through digital transformation. It integrates the value chain to enable functioning and optimization as a holistic system. The optimization is through the development of smart functionalities. This study uses qualitative research to determine the relationships between digital technologies, smartness, and organizational performance. It uses the research process to determine the performance metrics for Industry 4.0 and creates an Industry 4.0 business capability model to reflect its value-creation process.

4.4 Methodology

This study aims to formulate theory from practice and generate insight with practical usefulness. Industry 4.0 emerged and developed largely through the effort of industry actors (Verhoef et al., 2021). The industry has also outpaced academia in the digital transformation sphere resulting in theoretical gaps in support of industry practices. Furthermore, an analysis of existing literature revealed insufficient coverage of socio-technical systems in digital transformation (Liere-Netheler et al., 2018). As this study aims to explore existential phenomenology, the approach of exploring lived experiences of a relevant group to capture knowledge for theory development is justifiable (Collingridge & Gantt, 2008; Wang, 2022). Qualitative methodology is appropriate because it is effective for theory formulation to bridge gaps in the literature (Edmondson & McManus, 2007). Qualitative approaches are also useful for exploring experiences using natural language for data capture and translation to theory (Levitt et al., 2018); in this instance, a semi-structured interview of industry experts was employed. The interview framework is presented in Appendix A. The semi-structured interview provided the flexibility to explore each expert's unique experiences and insights while maintaining the same breadth of questions and similar depths of exploration across the interviewees (Saunders et al., 2009). Semi-structured interviews are also appropriate where the respondent's expertise is material (McIntosh & Morse, 2015).

The study aimed to access practitioners' deep industrial digital transformation knowledge bases. Thus, senior personnel of global technology firms who provide key technologies and services to global industrial organizations was targeted for participation. Sixteen respondents from seven organizations participated as convergence was achieved at sixteen interviews when no new concepts were observed. The smallest of these organizations by revenue had over USD 30B in revenue in 2021. The participants had a minimum of twenty-one years of relevant experience in digital transformation and belonged to the senior management cadre. Snowballing sampling technique was employed to facilitate triangulation (cross-checking responses among participants from the same organizations and similar industry affiliations) and enhance research validity (Etikan et al., 2016; Kitto et al., 2008). An overview of the respondents' profiles is presented in Appendix C – Participant profiles.

Coding and analysis followed the Gioia methodology (Gioia et al., 2013). The Gioia methodology builds perspectives on a subject matter through an iterative contextual analysis process that develops higher-order concepts from lower-order ones. It is effective for navigating diverse concepts to develop a data structure for understanding a subject matter in relatively short iterations (Gehman et al., 2017). The methodology consists of three stages through which the researcher applies consistent treatment to interview responses to arrive at a reliable outcome. The first stage is the first-order analysis. The principles of open coding (Strauss & Corbin, 1998) are applied, extracting concepts that preserve the original thought of research participants (Gioia et al., 2013). Open coding principles align with grounded theory methodology (Strauss & Corbin, 1994). The researcher extracts theory from data rather than imposing existing theory on the data, facilitating the original objective of existential phenomenology. The first-order analysis stage generates a lot of concepts that feed the second stage, the second-order analysis phase. In this phase, the researcher identifies emerging concepts based on logical associations among the first-order concepts. This is achieved by applying the researcher's conceptual perspectives on the first-order concepts (Shkedi, 2004), including consideration of the contexts in which the concepts were discussed. This study's conceptual perspective relates to performance and value creation. The final phase of analysis involves another iterative cycle through the second-order concepts, this time applying applicable theoretical lens to identify aggregate dimensions that define a data structure for the subject matter. Systems theory is the overarching theoretical foundation for this study. The model of systems presented by Dutta et al. (2005a) provides a guide, identifying inputs, capability as the intermediate outcome with enabling functionality, and system outputs.

To illustrate the application of the Gioia methodology in this study as an example, we consider the respondents' references to enhanced collaboration between man and machines as a feature of Industry 4.0 and the identification of collaborative robots as its key enabler. The first-order concepts capture the respondents' thoughts as natively and verbatim as possible, identifying man-machine collaboration and cobots as concepts. To derive the second-order concepts, the researchers apply the lenses of performance and value creation to the first-order concepts. These are the conceptual perspectives of the study. They enable the second-order concepts to answer the question, ‘how do the respondents attribute value creation to the first-order concept?’ It results in ***Digital Technology*** and ***Task Transformation*** as second-order concepts. To derive the aggregate dimensions, the researchers explore the second-order concepts from the lenses of the study’s theoretical basis, systems theory, and the specific system model presented by Dutta et al. (2005a), situating the emergent concept as input, output, or intermediate capability. It identifies ***Digital Technology***, ***Productivity***, and ***Safety*** as aggregate dimensions.

Appendix B presents the emergent data structure from the analysis.

The validity of the research is important to achieve its objectives (Golafshani, 2003; Rolfe, 2006). The research employed an initial expert validation by research colleagues (Straub, 1989) consisting of researchers with expertise in digital transformation and qualitative methodologies. They provided inputs into the construction of the interview guide. The study also employed triangulation in the data collection, analysis, and interpretation process (Kitto et al., 2008), recruiting multiple respondents from each industry segment covered by respondents. Three researchers reviewed the coding, analysis, and final data structure.

4.5 Results

The first-order concepts derived from analyzing responses to the question “What is Industry 4.0?” are documented in Appendix B. The appendix also documents the second-order concepts and the aggregate dimensions derived through further iterative analysis of the concepts from the lenses of their functional contribution to the production organization. Six aggregate dimensions, discussed in the following sections, are identified in the study. The first is the digital technologies that enable Industry 4.0. The second dimension is the capabilities of Industry 4.0 that while the last four dimensions address the value propositions of Industry 4.0, productivity, customer experience, sustainability, and safety.

4.5.1 Technology use

The value of Industry 4.0 is attributable to emergent properties of the confluence of increasing maturities of many digital technologies, which enabled interoperability across the production value chain (Respondent 1). Twelve respondents (1, 3, 4, 5, 6, 7, 8, 9, 11, 13, 14, and 16) identified the role of digital technologies in Industry 4.0. They identified digitalization and integration as the primary objectives of applying digital technologies and information transparency as result of digitalizing and integrating. Respondent 3 stated that industrial production had experienced pockets of gains from automation and computing prior to Industry 4.0. It is noted, however, that the value of Industry 4.0 is in the utilization of technologies to achieve cyber-physical systems (cps):

> *It is revolutionary, resulting in efficiency and effectiveness gains through cps. (Respondent 3)*

Respondents 4 and 10 similarly attributed the Industry 4.0 value to using digital technologies to create cps. They approached cyber-physical integration from the IT-OT integration perspective:

> *Industry 4.0 is the extension of digitalization principles from IT to OT. IT has long transformed the business technology space of the enterprise. Now the OT space is being similarly transformed and integrated, creating a single digital enterprise. This transformation is dependent on advanced technologies, particularly sensors, robotics, virtual reality, and artificial intelligence. (Respondent 4)*

Other respondents viewed the resulting integration from applying advanced technologies from different lenses. Respondent 8 focussed on enabling the end-to-end integration of the enterprise, while respondents 5 and 7 linked the end-to-end integration to Industry 4.0 capabilities development. Respondent 9 focussed on linking the technology-enabled integrations to production value stating that:

Industry 4.0 is about integrating the physical and virtual worlds for the purpose of production processes advancement. … In the Industry 4.0 context, production systems can attain super efficiency. (Respondent 9)

Respondent 7 summarised the use of technology in Industry 4.0. They identified the link between technologies and capabilities development and value creation. According to the interviewee:

Industry 4.0 is a series of layered capabilities that deliver optimal socio-economic outcomes in industrial production. The layered capabilities are facilitated by advanced technologies that enable stimuli responsiveness, artificial intelligence, data processing, visualization, and robotic actuation. (Respondent 7)

4.5.2 Enterprise smartness

According to Respondent 5, Industry 4.0's resultant enterprise capability for value delivery is smartness built on value chain integration:

The implementation of these technologies enables the integration of the value chain and the factory elements resulting in three capabilities, smart products, smart factory, and smart supply chain.(Respondent 5)

Respondent 11 corroborates the link between integration and smartness; and established the Industry 4.0 value path from technology to smartness through digitization, integration, data capability, and information transparency:

Industry 4.0 is the digitization of all aspects of production processes, the vertical integration of the factory, and horizontal integration of the production ecosystem with IoT, Enterprise Information Systems, and autonomous functionalities. Digitization provides the platform for integration, while integration creates the capability for smart characteristics. The horizontal integration connects the entire value chain from suppliers to the consumers while the vertical integration connects the processes within the production enterprise.

Data is an important part of the Industry 4.0 idea; it is the lifeblood of Industry 4.0. Data related to all aspects of the production enterprise operations covering planning, production, and maintenance are made available in real-time, powering analytics and providing the intelligence required for smart operations. (Respondent 11)

Respondent 7 provides more context to creating the Industry 4.0 smart capabilities, indicating that Industry 4.0 technologies produce stimuli-responsiveness, intelligence, and enhanced data functionalities to facilitate the capabilities which deliver optimal socio-economic outcomes in industrial production.

Industry 4.0 is a series of layered capabilities that deliver optimal socio-economic outcomes in industrial production. The layered capabilities are facilitated by advanced technologies that *enable stimuli responsiveness, artificial intelligence, data processing, visualization, and robotic actuation. (Respondent 7)*

Respondent 2 describes Industry 4.0 as the use of smartness to address key challenges of industrial production, namely the requirement for mass product customization, variability in the production environment, and sustainability challenges:

Industry 4.0 emerged as a systemic response to fundamental challenges facing production enterprises because of evolving socio-economic realities over a period. First is the increasing demand to customize or individualize products and services to satisfy the changing needs of consumers. The second is the evolving challenge of energy and resource utilization in response to environmental requirements. The third is the volatility of production parameters requiring a higher capacity for flexibility in production enterprises. Industry 4.0 uses smart solutions to address the challenges. (Respondent 2)

Respondent 2 puts smartness central to Industry 4.0 as its core value-creating capability. According to Respondent 12, Industry 4.0 goes beyond employing smartness internally, but the organization becomes a smart entity, reflected in its external interaction with its customers.

The smart factory, supply chain, and product are Industry 4.0 capabilities developed by the digital transformation of the production enterprise. They address challenges of the variability of production parameters, the need for mass product customization, and increased sensitivity to production's environmental impacts, providing the enterprise with the capacity for flexible and autonomous functioning. Through vertical, horizontal, and engineering integrations, sufficient information transparency is achieved to make the enterprise smart (Respondents 2, 10, 11, 12, and 16).

The respondents presented Industry 4.0 as a value-creation mechanism. According to Respondent 16:

Industry 4.0 is about the creation of fully connected production value chains. The idea thus is to better the capabilities of linear value chain constructs. (Respondent 6)

The study identified four lenses for Industry 4.0 value creation, seen from stakeholders' viewpoints, Productivity, Sustainability, Safety, and Customer experience.

4.5.3 Productivity

According to Respondent 16, the integrated, non-linear value chains created by Industry 4.0 is more productive than their linear predecessor. The research identified productivity from four stakeholder perspectives, Employees, Government, Partners, and Shareholders. Task-level productivity impacts Employees and Shareholders. Respondents 5 and 9 identified improvement of work tasks through enhanced man-machine interactions, and Respondents 6, 7, and 12 identified the impact of autonomous actuation on work tasks. According to Respondent 1, Industry 4.0 has implications beyond the firm at the national and international levels. It impacts economic growth, sovereign manufacturing capability, and job creation with implications for Government. Respondent 1 stated:

> *We will experience the classic hype cycle effect. The level of investment required to drive it to fruition will be difficult to achieve at this point. It will improve manufacturing in first-world countries because of lower cost manufacturing. It will push the pursuit of more sustainable supply chain arrangement, away from the constant pursuit of lower costs. (Respondent 1)*

Industry 4.0 impacts enterprise (organizational) production capabilities (Respondents 2, 3, 8, 12, and 16). Respondent 2 identified that Industry 4.0 develops organizational capabilities that deliver outcomes for the firm. Respondents 3, 8, 9, and 12 identified organizational level productivity impact of the Industry 4.0 capabilities. Respondent 9 stated, *“in the Industry 4.0 context, production systems can attain super efficiency.”*

4.5.4 Customer experience

Respondent 6 put the value delivery to the customer as important to Industry 4.0, stating, “the basic business value of Industry 4.0 is customer, the ability to anticipate customer needs and deliver them rapidly.”

According to Respondents 2 and 8, product customization is one of the key objectives of Industry 4.0 and a major way through which it influences customer experience (Respondents 2 and 8). Respondent 2 identified the customer and the enterprise (shareholders) as beneficiaries of the customer experience value, stating, *“Industry 4.0 enables mass product* *customization, simultaneously delivering value to the producer and consumer as productivity and superior customer experience."*

Respondents 8, 12, and 16 further reiterated the significance of mass product customization in Industry 4.0 through the enterprise transformations initiated to facilitate it, including product lifecycle transformation and persistent engagement of the customer.

4.5.5 Sustainability

Sustainability concern is one of the key factors that necessitated Industry 4.0. According to Respondent 2, three challenges necessitated Industry 4.0, and one was:

> *The evolving challenge of energy and resource utilization in response to environmental requirements. Through smartness, Industry 4.0 addresses the challenges that necessitated it. … It optimizes resource utilization and environmental interaction of production systems. (Respondent 2)*

Industry 4.0's sustainability impact includes socio-economic growth (Respondent 2), resource utilization in production processes (Respondents 5, 9, 12, 13, 15, and 16), environmental impacts of production processes (Respondents 5, 6, 7, 9, 10, 11, 12, 13, 15, and 16), and facilitation of social equity through consumptive business models which reduces setup costs for lower resourced producers by converting capital costs to operating costs (Respondent 14).

The study identified unique sustainability impacts through sovereign manufacturing capability Respondent 1 linked the emergent sovereign manufacturing capability from Industry 4.0 and sustainable supply chains. According to the interviewee, the impact on outsourcing dynamics between well-developed and lesser-developed nations will create sustainable supply chain arrangements, stating, "*it will push the pursuit of more sustainable supply chain arrangement, away from the constant pursuit of lower costs."*

Respondent 14 identified the similarity between cloud factories for manufacturing and cloud computing for digital infrastructure. According to the interviewee, cloud technologies enable consumptive business models. It facilitates social equity and democratizes access to opportunities, stating, "*Industry 4.0 actualizes the cloud factory concept which democratizes production infrastructure in the same way cloud computing does for digital infrastructure." (Respondent 14).*

4.5.6 Safety

According to Respondents 3 and 15, worker safety is a value proposition of Industry 4.0. Respondent 3 stated, *"Industry 4.0 increases productivity, product and process quality, cost optimization, product innovation, and employee safety." Respondent 15 stated,* "The value created by the integrated intelligent systems include organizational and occupational safety and productivity."

Work process transformation (Respondents 12 and 13) eliminates hazards, making them safer. Enhanced man-machine collaboration reduces physical and cognitive loads on workers (Respondents 5 and 9), and it introduces technologies with safety-enhancing functionalities (Respondents 2, 7, and 12). Respondent 3 stated that they had witnessed Industry 4.0 save a worker's life through tracking technologies that monitor the status of workers in real-time and reported an isolated worker who had collapsed, stating, *"I have witnessed a worker's life saved by Industry 4.0 technology with a man-down alarm going off."*

4.5.7 Conceptual framework

Based on the results, Figure 4.1 depicts conceptual model arising from this study, revealing the progression of utility from technologies to value creation.

Respondent 3 established a foundation for the thought process on Industry 4.0 value creation by stating that performance gains related to automation predated Industry 4.0. As such, the value proposition of Industry 4.0 is not in the application of technologies to automate processes. Respondent 14 reiterates the existence of automation and its application in industrial production before Industry 4.0. Respondents 3, 4, 9, 10, and 14 posited that the value is tied to cyber-physical integration built on digitization, which Respondent 9 characterized as *integrating the physical and virtual worlds*. They positioned information transparency as an additional layer of value on automation brought on by Industry 4.0. Respondents 5 and 11 progressed the thought processes by arguing that producers create value by exploiting the data and information resources presented by integration to generate smartness. According to respondent 11, contextual data about all production elements facilitated by end-to-end value chain integration are the basis for smartness. The value creation process of Industry 4.0 thus involves the derivation of information transparency from integration and smartness from information transparency. Beyond real-time information, transparency enables information flexibility, providing access to information beyond real-time through simulation, extended reality (Respondents 4 and 11), and predictive analytics (Respondents 5, 11, and 13).

Respondents identified value attributes of smartness to include autonomous functionalities (Respondents 12 and 13), optimized actions (responses, decisions, and actuations) (Respondents 2 and 13), and flexibility of processes (Respondent 13).

Sections 4.3 to 4.6 established that smart functionalities in production organizations improve the performance related to productivity, sustainability, customer experience, and safety resulting in the framework described in Figure 4-1.

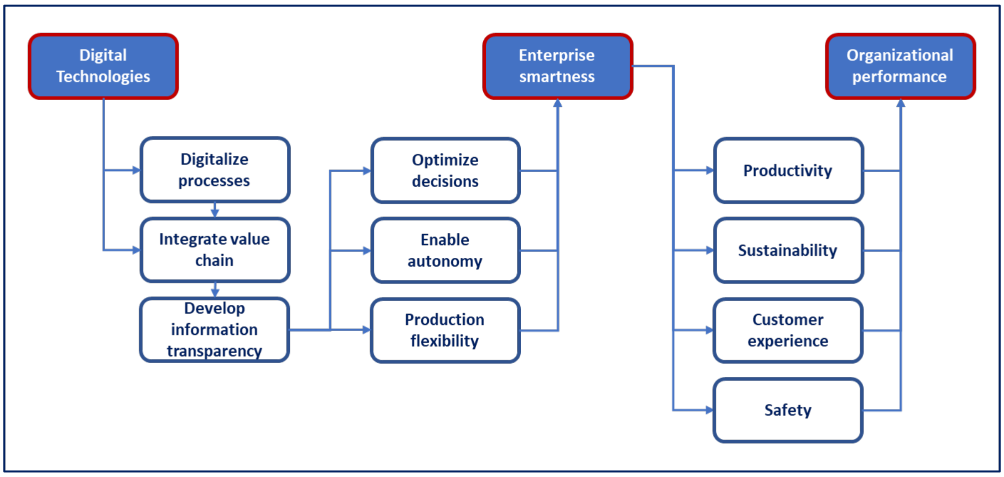

Figure 4-1 - Industry 4.0 conceptual model for organizational performance enhancement

4.6 Discussion and conclusion

The study examined how to drive organizational performance through Industry 4.0 and identified smartness as a critical link. It examined the value creation process of Industry 4.0. Integrating the value chain enables it to function as a single system that can provide better utilities than its parts could do on a reductionist basis. The results confirmed that integrating the value chain using digital technologies develops smart capabilities that optimize its operations and create performance enhancements. The study identified the performance impacts of Industry 4.0. Driving the holistic approach to value realization

The premise of Industry 4.0 value creation is based on the relationships between the degree of integration, the quality of information transparency, and the amount of smartness. Smartness is indicated by the quality of decision-making and actuation (including speed and accuracy) and the flexibility of processes.

The study provides additional context to existing studies that established Industry 4.0 as a performance improvement mechanism for industrial production through the application of technology (Dalenogare et al., 2018; Ghadge et al., 2020; Szász et al., 2020). Dutta et al. (2005a) describe capability as a system’s capacity to translate inputs into outputs. This study identified smartness as the capability in the Industry 4.0 context, translating digital transformation into performance gains. Smartness has been identified in studies as a feature of Industry 4.0 (Radziwon et al., 2014; Sjödin et al., 2018a; Wu et al., 2016; Zawadzki & Żywicki, 2016) describing the functionality of operational characteristics of the factory, supply chain, and products in the Industry 4.0 paradigm. This study identified the role of smartness in the value creation process and a product of a holistic design and operations framework for industrial production.

Furthermore, studies have predominantly quantified Industry 4.0 development by measuring aspects such as strategy, organizational culture, and technology (Kırmızı & Kocaoglu, 2022; Lassnig et al., 2021; Ramanathan & Samaranayake, 2021; Santos & Martinho, 2020; Veile et al., 2019). Existing trends associate digital maturity with the scope and scale of implemented technologies (Tutak & Brodny, 2022). Such efforts represent inputs into the digital transformation process and are not automatically reflective of outcomes; smartness is the organizational capability that effectively reflects value creation. Managers thus must target digital transformation efforts to improve enterprise smartness which would also be an appropriate measure of digital transformation maturity.

The study made a theoretical contribution to the manufacturing technology management literature by providing an Industry 4.0 systems model that established a relationship between technology, enterprise smartness, and organizational performance.

Despite its contribution, future research should involve quantitative studies to provide further empirical validation of its relationship with organizational performance and test the model quantitatively. Future studies could also focus on particular industries where trends across various industries can increase the generalisability of findings. It can also span various countries and involve cross-comparisons between countries at different levels of development to explore the impact of industry 4.0 on the smartness and performance of their organizations.

4.6.1 Managerial implications

The findings of this study provide implications for managers. According to the findings, these actions would be vital to driving organizational performance through industry 4.0.

Respondents opined, "*Data is an important part of the Industry 4.0 idea; it is the lifeblood of Industry 4.0*". Therefore, executing the Industry 4.0 paradigm implies that production organizations must uplift their data capability. Managers must ensure that key aspects of data capability, including data asset capture, governance, and utilization for developing autonomous functionalities and improved decision-making. Furthermore, the study identified information transparency, the ubiquitous availability of contextual information on all aspects of production, as central functionality to Industry 4.0 value creation. Developing the organizational data capability involves technology implementation, new management processes, and culture change. Managers must ensure that data capability uplift is well-resourced and driven with senior leadership support for Industry 4.0 success.

Competition for scarce investment resources will pressure managers to pursue short-term reductionist approaches. Respondents argued that "*the level of investment required to drive it to fruition will be difficult to achieve at this point*". Investments must be initially channelled to aspects of Industry 4.0 that contributed to smartness and those that delivered the quickest. To actualize the holistic systems approach, managers must take a more nuanced approach to end-to-end value chain transformation by dividing the value chain and prioritizing aspects that deliver quicker and more significant returns on transformation investments.

For example, the automotive industry started its digital transformation journey with factory autonomous functionalities before progressing to address smartness opportunities in the supply chain and products (Lee et al., 2023). Factory smartness delivered business gains through production efficiencies and product quality, enabling investments in more sustainable and feature-rich supply chains and products in subsequent investment cycles.

Respondents posited, "*Industry 4.0 will push the pursuit of more sustainable supply chain arrangement, away from the constant pursuit of lower costs*". The study's outcome implies that managers have more opportunities to pursue sustainability and long-term value for the broad stakeholder base under the Industry 4.0 paradigm and should utilize it. The study determines that Industry 4.0 will help optimize production costs and lessen the influence of cost pressures on ecosystem arrangements, leaving room for managers to pursue longer-term value realization. For example, managers will no longer feel pressured to outsource aspects of production to factories in places with poorer protections for workers or the environment due to cost considerations.

The study identified IT-OT integration as an underpinning structure for the end-to-end value chain integration and a running theme for Industry 4.0. IT and OT are historically siloed structures, representing separate people organizations, business processes, systems, and thought processes. Technology alone will not achieve the needed integration. To facilitate this integration, managers must devise organizational structures, management frameworks, and culture change programs. For instance, agile methodologies in project organizations have been identified as helpful in breaking existing silo walls between IT and business units (Colavita, 2016).

Product transformation through smartness is a core part of the Industry 4.0 value creation process. It leverages persistent customer integration to connect products' production and operations contexts into a cyclic lifecycle. Managers must facilitate the product lifecycle transformation through enhanced customer and product lifecycle management functionalities. This typically involves implementing better customer relationship management (CRM) and project lifecycle management (PLM) systems. It also involves developing better processes and aligning organizational structures to support the new product lifecycle paradigm.

This study has presented a unique framework for achieving organizational performance through Industry 4.0 by adopting a systems perspective for generating smartness as an organizational capability.

5 INVESTIGATING INDUSTRIAL DIGITAL TRANSFORMATION VALUE PROPOSITION

Journal submission: *This chapter was submitted for publication in the Journal of Computer Information systems: Abiodun, T., Rampersad, G.C. and Brinkworth, R., "Industry 4.0 Value Proposition: Evaluating Industry 4.0 maturity and its impact on outcomes" (under review). The Student's contribution was the majority of the publication (95%), specifically research design, data collection, analysis, and writing. The supervisors had a guiding, review, and editing role (5%).*

5.1 Abstract

Industry 4.0 promises to address key performance challenges of industrial production through digital transformation (IDT). Strategizing for IDT is challenging, and establishing its value proposition is non-trivial because of its complexity. This study investigated the value proposition of IDT by determining the impact of its maturity on organizational outcomes. This study makes a theoretical contribution of an IDT maturity model based on enterprise smartness, unlike previous ones based on technological and management efforts. The study employs a quantitative study of manufacturers by surveying 262 manufacturing professionals, using structural equation modeling to determine the relationships between technology use, enterprise smartness, and organizational outcomes. The study finds that technology use develops a smart enterprise, translating to performance gain. It further shows that factory smartness significantly impacts productivity, sustainability, safety, and customer experience outcomes. The study equips business managers with a valuable decision support tool for IDT strategy formulation, maturity assessment, and evaluation of transformation initiatives.

Keywords: Maturity modeling, smart manufacturing, digital transformation

5.2 Introduction

Industrial digital transformation (IDT) is proposed as the strategy for the fourth industrial revolution (4IR) (BMBF, 2014; Lichtblau et al., 2015). It is characterized by ideas such as smart manufacturing (Kusiak, 2018; Winkelhaus & Grosse, 2020) and the industrial Internet of Things (IIoT) (Boyes et al., 2018). It utilizes digital technologies to integrate the value chain end-to-end to deliver a smart enterprise that optimizes outcomes (BMBF, 2014; Lichtblau et al., 2015; Schuh et al., 2017).

IDT is a technology-driven value delivery mechanism (Xu et al., 2021). The early narratives of Industry 4.0 position IDT as embedding digital technologies in production processes to enable smartness in the production enterprise, translating to better organizational performance (BMBF, 2014; Lichtblau et al., 2015). Technology induces smartness as organizational capability in industrial producers to deliver outcomes; the value path thus goes from technology use through enterprise smartness to organizational outcomes, as shown in Figure 5.1.

Figure 5-1 - IDT value path

Industrial digital transformation can deliver operational efficiency (Kumar & Kumar, 2019), product innovation (Waris et al., 2017), and environmental sustainability goals (Ghobakhloo, 2020) in industrial production. Studies have identified strategy as a challenge for IDT implementation, with managers having difficulty navigating the complexity, determining the starting point, and the appropriate paths to value delivery (O'Donovan et al., 2016; Szalavetz, 2019). An important piece of the strategy formulation challenge is justifying the value proposition of the digital transformation effort in the context of the organization's specific objectives (Georgios et al., 2019; Müller, 2019). This study establishes the value proposition of IDT by determining the impact of its maturity on organizational outcomes. This address calls in the literature for more research exploring organizations' digital transformation journey or maturity to achieve outcomes (Li et al., 2022; Verhoef et al., 2021).

The study seeks to address its objective by reviewing the literature on maturity models to develop a holistic one for IDT. It explores information systems and management literature to identify the relevant performance metrics for IDT through the organizational impacts of digital transformation. The study then employs a quantitative research process involving a survey of manufacturing managers for data collection. It then develops a model for evaluating the maturity of IDT at the organizational level, using structural equation modeling to establish causal relationships.

The study makes a valuable theoretical contribution in developing a model for evaluating IDT maturity in organizations that focuses on outcomes rather than efforts, which is typical in existing literature, to improve the accuracy and practical relevance of the model. The study makes a vital practical contribution of a decision support tool for digital transformation planning and strategy formulation for business managers to support IDT capabilities development.

5.3 Literature review

5.3.1 Capabilities and maturity modeling

The value proposition of IDT to organizations can be established by determining its impact on organizational outcomes. Such determination requires quantifying organizational IDT. The approach to quantifying IDT due to the structural complexity and non-standardization of digital production systems is an important management issue (Mourtzis et al., 2019). Quantification is also challenging because the impact of implemented technology is often difficult to measure due to the multiple factors involved, including business processes efficiency, quality of systems implementation, and user inputs (Haider et al., 2006).

Focussing on capabilities provides a solution to the challenge of quantifying IDT. Systems can be modeled as inputs, (intermediate) capabilities, and outputs (Dutta et al., 2005a). Capabilities can be considered the efficiency with which a system utilizes inputs or converts them into outputs (Dutta et al., 2005b). It is also established in theory that IDT creates value through capabilities, and the value of technologies in IDT is the capabilities they enable (Szalavetz, 2019). The utility of inputs is thus appropriately quantifiable by measuring capabilities, and there is a potential accuracy gain by building IDT measurement models on outcomes (capabilities) over models that measure inputs or efforts (technology and management).

Capabilities drive organizational performance (Teece, 2019; Teece et al., 1997), and enterprise smartness is the intermediate capability created in the IDT context where technologies and management components, including strategy, leadership, and culture, are the inputs and organizational performance is the output (BMBF, 2014; Lichtblau et al., 2015; Schuh et al., 2017). The value of ordinary capabilities to organizations is limited, as they cannot sustain competitive advantages (Teece & Pisano, 2003). Sustaining competitive advantages thus requires the creation of dynamic capabilities for the organization. Such capabilities can address emergent challenges in the organization's operating environment by shaping and responding to the rapid changes in the business environment (Teece, 2014). The value proposition of IDT is tied to its ability to address dynamic challenges like variability in the production environment through disruptions and changing requirements (Dequeant et al., 2016; Smorodinskaya et al., 2021) and evolving customer needs, including product personalization, automated support and maintenance, and continual improvement (Aheleroff et al., 2019; Tseng & Jiao, 1997). The intelligence and stimuli-responsiveness that characterize smart production systems (Fragapane et al., 2020) enable sensing, seizing, and transforming resources, features of dynamic capability for sustained value creation.

Maturity models are a useful capability measurement mechanism; they measure capabilities by defining their practical dimensions and how each dimension evolves (Domingues et al., 2016). They further prescribe a logical, sequential, and graduated path from the lowest level of evolution to the highest level (Röglinger & Pöppelbuß, 2011). The maturity path is established by classifying a target capability's level of sophistication or operational embeddedness (Bititci et al., 2014). The classification partitions the development into a spectrum, spanning the distance between the least possible level of advancement to the most feasible advanced development state, representing its relative state of perfection (Nikkhou et al., 2016).

Maturity models often have flaws. They are typically arbitrary in design, lacking empirical foundations in structuring the maturity spectrum and determining the target capability's dimensions (Blondiau et al., 2013). Different models can often determine different maturities for the same entity using different models (Akinpelu et al., 2021). Given that the alignment of maturity models with the target capability's design principles indicates model quality (Dikhanbayeva et al., 2020), it is problematic that many models have poor alignment between model and reality. This misalignment results in poor performance when the models are used to predict reality (Mittal et al., 2018). This study makes an important theoretical contribution by developing an Industry 4.0 maturity model that closely mirrors industrial production based on robust empirical testing.

An analysis of data from Dikhanbayeva et al. (2020), which compared the major digital transformation maturity models, indicates that existing models are predominantly effort-based: they measure the effort deployed in achieving an objective and thus characterize the system mainly by its inputs. Effort models implicitly assume that effort results in expected outcomes without empirical validation. This assumption is invalid for generalized digital transformation models because production systems are complex (Herrera Vidal & Coronado Hernández, 2021). Furthermore, completing project tasks does not guarantee project success (Martens et al., 2018). This study devises a novel approach to IDT maturity modeling by measuring enterprise smartness (intermediate capability or outcome) instead of technology and management functions (effort) components in previous studies (Dikhanbayeva et al., 2020; Lichtblau et al., 2015). This study improves IDT maturity modeling by avoiding the implicit assumption that effort translates to outcomes. The IDT maturity model based on enterprise smartness reflects the utility of digital transformation in production environments more accurately, given that models' success is related to sufficiently mirroring reality (Poznic, 2016).

The Capability Maturity Model Integration (CMMI) and its predecessor, the Capability Maturity Model (CMM), are the most significant frameworks for developing maturity models (von Wangenheim et al., 2010); they are responsible for the most maturity models in academic literature. Empirical studies established that the CMMI-based process improvements delivered value on cost, schedule, quality, customer satisfaction, and investment return (Goldenson & Gibson, 2003). The CMMI is a framework for maturity modeling developed by the Software Engineering Institute (SEI) to extend the Capability Maturity Model (CMM). The CMMI is a means of maturing a holistic capability (Selleri Silva et al., 2015). In contrast to the CMMI, the CMM is a behavioral model focused on process maturity and was initially designed to guide software development and management processes (Paulk et al., 2011). The CMMI is versatile and has been applied to diverse processes and systems, including sustainable Information Technology (Patón-Romero et al., 2019), organizational training (Khraiwesh, 2020), process optimization (Rainho & Barreiros, 2019), and aerospace systems safety and security (Wood & Vickers, 2018). CMM/CMMI's background in technology and business process applications makes it a good fit for IDT.

The CMMI prescribes five levels of maturity - ***Initial***, ***Managed***, ***Defined***, ***Quantitatively Managed,*** and ***Optimizing*** (O'Regan, 2011; Torrecilla-Salinas et al., 2016).

5.3.2 IDT organizational outcomes

The digital transformation literature identifies IDT objectives that extend beyond the considerations of shareholders to cover the interests of a broader group of stakeholders. This section discusses how IDT addresses stakeholders' value propositions, including the general socio-economic environment (sustainability), shareholders (productivity), customers (customer experience), and employees (safety).

Sustainability: Contribution to sustainable business is one of the key expectations of Industry 4.0 (Prause, 2015). Industrial production has been an important driver of environmental, social, and economic sustainability challenges. A cause-and-effect relationship between sustainability challenges and technological capabilities was created because the resolution of sustainability challenges requires technology-enabled information transparency and optimal utilization of resources by production processes (Ghobakhloo, 2020; Lasi et al., 2014; Zhao et al., 2020). It is established that the pursuit of productivity through smart operations would optimize production resources, reduce emissions, and enable social value (Furstenau et al., 2020; Ghobakhloo, 2020; Li et al., 2017). Similarly, Machado et al. (2020) established a relationship between sustainable manufacturing and technology use that enables IDT to have an integrated impact on all aspects of sustainability.

Productivity: Productivity improvement is central to IDT value proposition (BMBF, 2014). Industrial productivity is concerned with production volume under specified conditions, including product quality, time, and resource utilization (Trojanowska et al., 2018). The extensive globalization of businesses created new challenges for production enterprises (Voronkova et al., 2020). Every industrial revolution employs technological advancements to improve productivity (Rüßmann et al., 2015). Industry 4.0 uses CPS to integrate the production value chain, enabling smart functionalities for addressing productivity challenges (Tao et al., 2019).

Customer experience: Existing product lifecycle paradigms had inherent limitations; they could not uniquely consider each customer and address them individually, representing a challenge for customer experience (Borangiu et al., 2019). IDT seeks to deliver better customer outcomes by engaging the customer early in the production process (BMBF, 2014). Early customer inclusion in the product lifecycle enables mass product customization capability by capturing unique requirements and feeding the design and production processes. It was identified as a distinctive IDT feature from its inception (BMBF, 2014; Borangiu et al., 2019; Li et al., 2017; Oztemel, 2018).

Safety: Technology has played a key role in industrial safety advancements (Badri et al., 2018; Siemieniuch et al., 2015). Industrial producers have progressively increased their commitments to worker safety and wellbeing over the last century (Hofmann et al., 2017). Digitally transforming the production enterprise entails transforming production tasks and the nature of work. The emerging nature of work implies less reliance on human physical effort (Adriaensen et al., 2019). Furthermore, advancements in technology-enabled human factors enable better management of cognitive load on human workers (Carvalho et al., 2020). These work and workplace changes are designed to improve workers' safety and wellbeing outcomes. Industry 4.0-related technologies have functionalities that deliver better safety for workers. They have been successfully implemented for autonomous preventative maintenance (Liu et al., 2020), collision avoidance (Bragança et al., 2019; Gochev et al., 2017), monitoring and tracking (Javed et al., 2021), and wearable technologies (Barata & Cunha, 2019; Romero et al., 2018). There are increasing expectations for changes in the production process and work design because of digitalization to deliver better workers' safety and wellbeing (Adriaensen et al., 2019; Sjödin et al., 2018a).

5.3.3 Key IDT maturity factors driving organizational outcomes

5.3.3.1 Technology use

The study recognizes that technology is deployed as a catalyst for capability development and that technology acquisition and implementation is not an end in itself in digital transformation (Szalavetz, 2019). Technology is thus the effort component of maturity, deployed to achieve outcomes. Furthermore, studies identified that digital transformation efforts fail when non-technical aspects such as strategy, culture, and leadership are ignored. Technology use, measured as the absolute total deployment of the said technology in business operations at a particular time (Battisti & Stoneman, 2003; Pulkki-Brännström & Stoneman, 2013), is an appropriate measure of the system's functional capability (Geyda, 2020; Geyda & Lysenko, 2020). Rather than evaluate the presence of technology in the organization, technology use reflects the level of embeddedness of technologies in business processes, encapsulating the technical and management competencies required to deliver technology capabilities within business processes.

Research on IDT-relevant technologies is not exhaustive (Zheng et al., 2021); This study avoids a detailed exploration of IDT technologies that are constantly evolving. Instead, it follows a technology-agnostic perspective to evaluate the impact of technology use, considering broad technological features based on requirements for smart systems. Smartness is core to IDT, and technology integration in production processes aims to make the production enterprise smart (BMBF, 2014; Lichtblau et al., 2015). The literature on smart systems identifies stimuli-responsiveness, intelligence, and data functionalities as core characteristics of smartness (Ferraris et al., 2019; Habibzadeh et al., 2018; Kernecker et al., 2020; Samimi-Gharaie et al., 2018; Zhou et al., 2019). Furthermore, the convergence of physical and virtual production elements creates requirements for simulation, visualization, and remote interaction capabilities unique to IDT (Damiani et al., 2018).

The technology use measure thus considers the embeddedness of technologies that address five groups of features critical to smartness in production operations. Stimuli-responsiveness spawned two classes, sensing, and actuation, to enhance clarity for research respondents.

- **Sensing** – Sensors, IoT, RFID,
- **Actuation** – Cobots, industrial robots, AGVs, etc.
- **Intelligence** – Machine learning, natural language processing, machine vision, etc
- **Data and information management** – Enterprise information systems, cloud, and edge computing, cyber security, etc
- **Simulation, visualization, and remote interaction** – Digital twins, virtual and augmented reality, live virtual construct etc.

IDT literature posits that integrating digital technologies in the operations of the production enterprise would make the supply chain, factory (production systems and processes), and product smart. However, while factory and supply chain smartness are generally relevant to production, product smartness is only selectively relevant as many industries have products such as food or chemicals to which a smart context is still to be defined or applied. Advanced digital technologies induce smartness in the supply chain, factory, and products by enabling sensing, actuation, intelligence, and data capabilities (Butner, 2010; Chen et al., 2018; Schmidt et al., 2015; Wu et al., 2016). However, the expectation of smartness is largely intuitive and unquantified and would benefit from empirical evidence. Therefore, we hypothesize:

1. Hypothesis 1: Technology use positively influences factory smartness
2. Hypothesis 2: Technology use positively influences supply chain smartness

5.3.3.2 Enterprise smartness

Smartness is a system's capacity to optimize outcomes through intelligence. Enterprise smartness thus measures the production enterprise's capability for optimization based on intelligence. Some studies have attempted to quantify smartness (Ghansah et al., 2020; Jadhav & Shenoy, 2020; Kádár, 2011). However, there is insufficient research in the Industry 4.0 context. The common themes in these attempts are the extent of autonomy and the optimality of outcomes. This study builds on Fragapane et al. (2020), who identified autonomy and flexibility as the qualitative characteristics of smart systems in the IDT context to evaluate the production enterprise's smartness. A system's autonomy is its ability to perform complex tasks in an unstructured environment without continuous human guidance (Radziwon et al., 2014; Schuh et al., 2019). The flexibility of the production enterprise is its agility (Ameri & McArthur, 2013). It is its capacity for rapid adjustments through changes or rearrangements to its systems architecture to address new product requirements, new production process requirements, changes in the production environment, scalability for changing capacity requirements, and changes in the supply chain (Abdi, 2018; Radziwon et al., 2014; Schuh et al., 2019).

IDT is appropriately rationalized as horizontal, vertical, and end-to-end engineering integrations (Bartodziej, 2017; Wang et al., 2016). These integrations correspond to the parts of the production value chain, i.e., the supply chain, production processes, and products (Nagy et al., 2018). Thus, the nuances of interaction between the smartness of the supply chain, production processes, and products and safety, sustainability, productivity, and customer experience need further attention.

To evaluate IDT maturity, we measure the autonomy and flexibility of the supply chain and the factory based on the five maturity levels prescribed by the CMMI. This study aims to achieve generalizable results; thus, it does not consider product smartness as a factor, given that participation is expected from industries whose products are not associated with smartness, including food and beverages, pharmaceuticals, and chemicals.

5.3.3.3 Factory (production systems and processes) smartness

This is the capability for production based on the autonomous functioning of the Industrial Internet of Things (IIoT) or the network of production entities, including people, devices, systems, and products. The production system has the capacity for reconfigurability and integrates the production and operation phases of the product lifecycle for continual improvement (Chen et al., 2018; Radziwon et al., 2014). Factory smartness facilitates optimal decision-making (Goryachev et al., 2013), utilization of production resources (Hawkins, 2021; Kumar et al., 2021), the transformation of work tasks to optimize production processes (Bragança et al., 2019), and product customization (Sinha & Roy, 2020; Sjödin et al., 2018a)

Factory smartness drives productivity by optimizing decision-making and resource utilization (Goryachev et al., 2013), transforming work tasks, and improving product quality. The optimization of resource utilization also drives sustainability by reducing material and energy consumption (Hawkins, 2021; Kumar et al., 2021). Integrating the production and operation phases of the product lifecycle embeds the customer early and perpetually into the production process. It facilitates mass product customization, proactive product support, and dynamic product improvement (Sinha & Roy, 2020; Sjödin et al., 2018b), resulting in improved customer experience. The smart factory also uses digital technologies to transform work tasks, reducing hazards to humans at work (Bragança et al., 2019) and providing new functionalities that enhance worker safety (Islam et al., 2022; Li, 2016).

Therefore, this research includes the following hypotheses:

3. Hypothesis 3: Factory smartness positively impacts productivity
4. Hypothesis 4: Factory smartness positively impacts sustainability

5. Hypothesis 5: Factory smartness positively impacts customer experience
6. Hypothesis 6: Factory smartness positively impacts safety

5.3.3.4 Supply chain smartness

The smart supply chain is an autonomous network of functions that support production logistics (Wu et al., 2016). It is characterized by its ability to respond autonomously and efficiently to disruptions and facilitate information transparency across the entire production chain (Gupta et al., 2019; Sodhi & Tang, 2019).

Productivity and sustainability enhancements in Industry 4.0 are related to the optimization of resource utilization and decision-making (Goryachev et al., 2013; Hawkins, 2021; Kumar et al., 2021). The smart supply chain enables optimization through autonomous functionalities that reduce human mediation (Pasi et al., 2020). The smart supply chain also supports enhanced customer experience and safety through information transparency (Sodhi & Tang, 2019; Tripathi & Gupta, 2020). Furthermore, smart supply chains enhance safety through hazard identification and elimination in tasks using digital technologies (Tang & Veelenturf, 2019) and platforms (Veile et al., 2022).

We, therefore, hypothesize the following:

7. Hypothesis 7: Supply chain smartness positively impacts productivity
8. Hypothesis 8: Supply chain smartness positively impacts sustainability
9. Hypothesis 9: Supply chain smartness positively impacts customer experience
10. Hypothesis 10: Supply chain smartness positively impacts safety

Drawing on these hypotheses, the conceptual model developed in this study is shown in Figure 5.2.

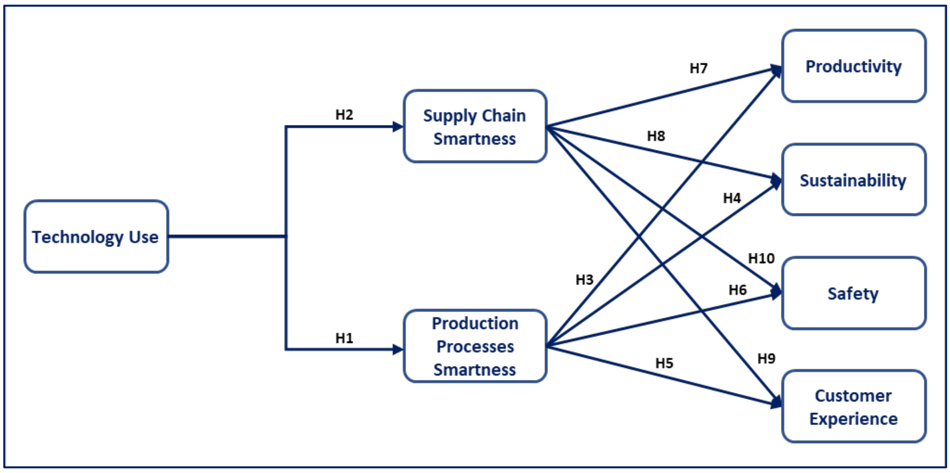

Figure 5-2 - Conceptual model developed in this study

5.4 Methodology

5.4.1 Data collection

We developed and tested a conceptual model using a quantitative survey that targeted manufacturing managers. As this study aimed for broad generalization, it was important to achieve research design that aids statistical generalization (Polit & Beck, 2010). Using social media for data collection in scientific studies is effective in such scenarios. It enhances participant engagement and creates opportunities for broader distribution (Leighton et al., 2021; Yuan et al., 2014). LinkedIn facilitated the targeting of respondents by multiple career-related parameters, while avoiding geographical and sectoral boundaries. This study required respondents to estimate CMMI capability levels for technology use, supply chain smartness, product smartness, and process smartness of their organization. It targeted respondents with degree-level education, current manufacturing-related job roles, a minimum of 10 years of industry experience, and English language profiles.

The survey was anonymous and active from November 2021 to February 2022, with participation invitations sent out using the LinkedIn campaign manager in English. There were 325 attempts to complete the survey, of which 262 responses were complete. The study utilized only fully completed responses.

The data was captured using a five-point Likert scale appropriate for capturing respondents' perceptions (Fowler, 2009, p. 100). Stemming from the factors described in Section 5.3, Table 5-1 details the questions used in the survey to establish Industry 4.0 maturity.

Factors		**Question**	**Response options**
Technology Use (Tech_Use)	Sensing	What is the CMMI level for the use of ***Sensors (Sensors, IoT, Embedded devices, RFID etc)*** in your organization?	• Initial • Managed • Defined • Quantitatively managed • Optimizing
	Actuation	What is the CMMI level for the use of Robotics (Digital fabrication, cobots, Industrial robots, Automatic Guided Vehicles (AGVs) etc) in your organization?	
	Simulation, visualization, and remote interaction (SVR)	What is the CMMI level for the use of Extended Reality (Virtual / Augmented reality, Digital twins, Live-Virtual Construct (LVC), Simulations etc) in your organization?	
	Data and information management (DIM)	What is the CMMI level for the use of Digital Infrastructure (Cloud / Edge Computing, broadband & NXG networks, Cyber security etc) in your organization?	
	Intelligence	What is the CMMI level for the use of Artificial Intelligence (Machine learning, Natural Language Processing, Predictive analytics etc)in your organization?	
Factory Smartness (Factory_SMT)		What is the CMMI level for ***Factory autonomy*** e.g., processes do not need human intervention, including for decision-making?	
		What is the CMMI level for ***Factory flexibility*** e.g., production processes can be changed e.g., to produce new products or change specifications of existing products, without building new factories or installing significant new machinery	
Supply Chain Smartness (SC_SMT)		What is the CMMI level for ***Supply chain autonomy*** e.g., Dynamic, intelligent handling of demand (routing, resource allocation) along the supply chain?	
		What is the CMMI level for ***Supply chain flexibility*** e.g., automated handling of disruption and demand changes along the supply chain?	

Table 5-1 - Maturity factors measurement

Table 5-2 details the questionnaire items for measuring organizational outcomes.

Factor	Measure	Response Options
Productivity (Moghimi, 2006)	Our production processes and systems are effective (they get the job done)	• Strongly disagree • Somewhat disagree • Neither agree nor disagree • Somewhat agree • Strongly agree
	Our production processes are efficient (they utilize resources well)	
	Our product quality is better than competitors	
Safety (Ostrom et al., 1993)	Our safety incidence record is better than our peers	
	Our safety process has senior leadership engagement	
Customer Experience (Klaus & Maklan, 2013)	Our customers are satisfied with our products and services	
	Our customers recommend us to others	
	Our customers are generally loyal to us	
Sustainability (Xie & Zhu, 2020)	Our company is effective at optimizing resource use (energy, water, and materials)	
	Our company is effective at minimizing our environmental pollution, including Carbon Dioxide emissions	
	Our company is ethical. We are committed to social good.	

Table 5-2 - Organizational factors measurement

5.4.2 Data analysis approach: Structural Equation Modeling (SEM)

Data were analyzed in this study using confirmatory factor analysis through Structural Equation Modeling (SEM). SEM is a multivariate statistical methodology for determining the causal relationships between variables (Elston et al., 2012, p. 495). It enables the representation of the hypotheses from theory as a model, constructed as structures that present the causal processes in a series of relationships between variables (Byrne, 2001, p. 3). SEM is a mix of two basic constructs; one relates latent variables to each other, and the second relates measurement variables to the latent variables they measure. Collectively, the underlying constructs paint a holistic picture of reality (Díaz-Chao et al., 2015). SEM is an appropriate mechanism for estimating the causal relationship between Industry 4.0

maturity and firm performance because they are both multivariate latent variables built out of observed variables. The R programming language's ***lavaan package*** (Oberski, 2014) was used to analyze the data. Other popular software solutions for handling SEM data include SPSS AMOS and Mplus, with similar accuracy levels (Narayanan, 2012). Lavaan was chosen over the other applications to utilize the R’s data analytics functionalities (Morandat et al., 2012).

5.5 Results

5.5.1 Descriptive statistics

The study was designed to provide generalizable results. Participants were restricted only by professional profiles that reflect English language ability, degree level education, a minimum of ten years experience in manufacturing, and a current manufacturing job. It is designed to ensure they can address questions such as manufacturing capabilities and organizational performance. More than 99% of the responses came from the world’s twenty most industrialized nations (Rahman et al., 2021). Based on the size of the companies, the responses were normally distributed with a slight positive skew. The bulk of the responses fell within the three middle company size groups. The middle group, one hundred and one employees to one thousand employees, recorded the most responses at approximately forty percent of all respondents. Table 5-3 presents a summary of the respondent’s distribution.

	Item	**Frequency**	**Percentage**
Country	Australia	19	7.25%
	Bangladesh	1	0.38%
	Brazil	16	6.11%
	Canada	18	6.87%
	China	16	6.11%
	France	24	9.16%
	Germany	38	14.50%
	India	37	14.12%
	Nigeria	1	0.38%
	UK	35	13.36%
	USA	57	21.76%
Total		262	100.00%
	Automotive	3	1.15%

Industries	Chemicals	5	1.91%
	Electronics	16	6.11%
	Food and	94	35.88%
	Heavy equipment	5	1.91%
	Household goods	31	11.83%
	Metals and	14	5.34%
	Not Specified	27	10.31%
	Pharmaceuticals	67	25.57%
Total		262	100.00%
Company size (Employee count)	(1 - 10)	21	8.02%
	(11 - 100)	40	15.27%
	(101 - 1000)	104	39.69%
	(1001 - 5000)	45	17.18%
	(> 5000)	52	19.85%
Total		262	100%
Respondents Industry 4.0 knowledge	None	15	5.73%
	Little	35	13.36%
	Average	83	31.68%
	Very Good	90	34.35%
	Excellent	39	14.89%
Total		262	100%

Table 5-3 - Summary of responses

5.5.2 Reliability and validity

Reliability and validity of measures address the consistency and accuracy of measures, respectively (Churchill Jr, 1979). Measures should be consistent, producing similar outcomes under consistent conditions. Measures must also be accurate, i.e., report what they purportedly do. The reliability of congeneric models was determined before the construction of the full SEM. By convention, factor loadings must exceed 0.5 (Steenkamp & van Trijp, 1991), which is satisfied in all the factors. Table 5-4 presents the factor loadings from the congeneric models developed for exploratory factor analysis.

Construct	Items	Factor Loadings
Tech_Use	Sensing	0.725
	Actuation	0.691
	SVR	0.713
	DIM	0.742
	Intelligence	0.686
SC_SMT	Chain Autonomy	0.782
	Chain Flexibility	0.684
Factory_SMT	Process Autonomy	0.789
	Process Flexibility	0.842

Productivity	Production Effectiveness	0.807
	Production Efficiency	0.825
	Product Quality	0.819
Safety	Safety Incidence Performance	0.828
	Safety Senior Leadership Engagement	0.681
Customer	Customer Satisfaction	0.872
	Customer References	0.661
	Customer Loyalty	0.670
Sustainability	Economic (Resource use)	0.781
	Environmental (Pollution)	0.982
	Social (Ethics and Social Responsibility)	0.968

Table 5-4 - Factor loadings of congeneric model

Coefficient alpha (α) (Cronbach, 1951) and construct reliability (ω) (coefficient omega with unit weights) (Cho, 2021; McDonald, 2013) are widely used to measure reliability, and measures are considered reliable if coefficient alpha and construct reliability exceed 0.7 for factors (Hair et al., 2006; Kline, 2005).

	Coefficient alpha (α)	**Construct Reliability (ω)**
Tech_Use	0.83	0.84
SC_SMT	0.70	0.70
Factory_SMT	0.79	0.79
Productivity	0.86	0.85
Safety	0.72	0.71
Customer	0.79	0.77
Sustainability	0.93	0.94

Table 5-5 - Reliability measure

The reliability for all constructs reflected sufficient reliability of measures, according to Table 5-5. Equation 1 and Equation 2 present the formula for Coefficients Alpha and Omega, respectively.

$$\alpha = \frac{k}{k-1}\left[1 - \frac{\sum_{i=1}^{k}\sigma_{ii}}{\sum_{i=1}^{k}\sigma_{ii} + 2\sum_{i<j}\sigma_{ij}}\right]$$

Equation 1 - Crombach's Coefficient Alpha

Where:

- ***k*** is the number of items in a construct,

- σ_{ii} is the item ***i*** observed variances, and,
- σ_{ij} is the observed covariance of items ***i*** and ***j***.

and:

$$\omega = \frac{\left(\sum_{i=1}^{k} \lambda_i\right)^2}{\left(\sum_{i=1}^{k} \lambda_i\right)^2 + \sum_{i=1}^{k} \psi_i}$$

Equation 2 - Construct Reliability (Coefficient Omega)

Where:

- λ_i is the factor loading of item ***i***,
- ψ is the uniqueness of item ***i***,
- ***k*** is the number of items in the factor

Similarly, validity was evaluated using convergent and discriminant validity. Convergent validity evaluates the correlation amongst measures of the same construct, while discriminant validity establishes each measure's distinctiveness from other measures (Kline, 2005). Construct validity and discriminant validity are measured according to Fornell and Larcker (1981). Construct validity is calculated using the average variance extracted (AVE) (Equation 3). It is established where AVE is greater than .0.5. Discriminant validity is established where the square root of the AVE for each construct is lesser than the maximum shared variance (MSV).

Table 5-6 shows that all the constructs have convergent and discriminant validity. The AVE was calculated using R, while MSV was calculated from the Pearson correlation coefficients from SPSS analysis.

	AVE	**√AVE**	**MSV**	**Construct Validity (AVE > 0.5)**	**Discriminant Validity (√AVE > MSV)**
Tech_Use	0.506	0.711	0.409	Established	Established
SC_SMT	0.535	0.732	0.459	Established	Established

Factory_SMT	0.658	0.811	0.695	Established	Established
Productivity	0.649	0.805	0.592	Established	Established
Safety	0.554	0.744	0.685	Established	Established
Customer	0.539	0.734	0.562	Established	Established
Sustainability	0.831	0.911	0.695	Established	Established

Table 5-6 - Validity measure

$$AVE = \frac{\sum_{i=1}^{p} \lambda_i^2}{\sum_{i=1}^{p} \lambda_i^2 + \sum_{i=1}^{p} Var(\varepsilon_1)}$$

Equation 3 - Average Variance Extracted (AVE)

Where:

- ***p*** is the number of items,
- ***λ_i*** is the factor loading of item ***i***, and,
- ***Var(ε_i)*** is the variance of the error of item ***i***

5.5.3 Model fit

The model was tested for goodness-of-fit against the data. These indices assess the extent to which the model represents the data (Barrett, 2007). Multiple measures were employed to establish goodness-of-fit. Chi-square statistic ($\chi 2$) tests exact fit by considering the size of the differentials between measurements and the model's expected values. It is sensitive to sample and population sizes, and the acceptable significance level is $p > 0.05$ (Barrett, 2007). The normed $\chi 2$ test attempts to create a fit index with lesser sensitivity to sample size by dividing the $\chi 2$ by the degrees of freedom (df). The acceptance value of the normed $\chi 2$ is < 2 (Ullman, 2001). The Root Mean Square of Approximation (RMSEA) estimates *close fit* by measuring discrepancy per degrees-of-freedom (df). The model is considered fit if RMSEA is less than 0.05 (Brown & Cudeck, 1983; Byrne, 2016). The Tucker-Lewis Index (TLI) and the Comparative Fit Index (CFI) are incremental fit measures. They compare the fitted model to a base model, usually one where observed variables' variances are the only parameters (Hu & Bentler, 1995). While the CFI is constrained to values between zero and

1, the TLI can have values greater than one, and the model fit is acceptable with values greater than 0.95 (Byrne, 2016; Hu & Bentler, 1999). Standardized Root Mean Square Residual (SRMR) also measures the difference between the matrices of the model implied variances and covariances and sample observed variances and covariances, standardized to handle outliers, and the model is acceptable with an SRMR value < 0.08 (Hu & Bentler, 1999).

Results in Table 5-7 presents the statistical fit metrics indicating that the model fits the data.

Test	**Acceptance**	**Result**
Chi-square ($\chi 2$)		161.029
degrees of freedom (df)		154
pValue	> 0.05	0.333
Normed $\chi 2$ ($\chi 2$/df)	< 2	1.046
Standardized Root Mean Square Residual SRMR	< 0.08	0.064
Root Mean Square of Approximation (RMSEA)	< 0.05	0.013
Comparative Fit Index (CFI)	> 0.95	0.998
Tucker-Lewis Index (TLI)	> 0.95	0.997

Table 5-7 - Goodness-of-fit measures

5.5.4 Normality

This study utilized the Lavaan package of R, which employs maximum likelihood estimation for SEM. Thus, the data's normality is assumed (Fahrmeir & Kaufmann, 1985). The data for the measurement items were tested for normality by checking skewness and kurtosis (Cain et al., 2017). Skewness determines the extent of a distribution's asymmetry about its mean and whether it is *skewed* in one direction or another. Kurtosis determines how tailed a distribution is, indicating its symmetry. The skewness ranged between -0.155 and 0.340, and kurtosis ranged between 2.497 and 3.684. Both skewness and kurtosis were within the acceptable ranges (Hair et al., 2019). Sphericity tests were also conducted to establish sample adequacy using the KMO and Bartlett's tests (Hair et al., 2019). KMO value was 0.93, and Bartlett's test results were $\chi 2$ = 3217.625, *df* = 190, and *Sig* = 0.000. The results established sample adequacy.

5.5.5 Hypothesis tests

The results from the hypothesis testing are summarized in Table 5-9 and Figure 5.3.

Hypothesis	Independent Variable	Dependent Variable	Standardized Regression Coefficients	P(>|z|)	Outcome
H1	Tech_Use	Factory_SMT	0.602	0.000	Supported
H2	Tech_Use	SC_SMT	0.355	0.000	Supported
H3	Factory_SMT	Productivity	0.676	0.000	Supported
H4	Factory_SMT	Sustainability	0.762	0.000	Supported
H5	Factory_SMT	Customer Experience	0.679	0.000	Supported
H6	Factory_SMT	Safety	0.854	0.000	Supported
H7	SC_SMT	Productivity	0.382	0.000	Supported
H8	SC_SMT	Sustainability	0.265	0.000	Supported
H9	SC_SMT	Customer Experience	0.185	0.007	Supported
H10	SC_SMT	Safety	0.232	0.000	Supported

Table 5-8 - Results

The study was based on the premise that technology drives smartness and smartness drives performance, and smartness is the basis of IDT maturity. We explored the impact of technology use on smartness in the supply chain and the factory and their impact on organizational outcomes. Only relationships with $p < 0.05$ are deemed statistically significant; hence, these hypotheses were supported; others were considered statistically non-significant and unsupported (Andrade, 2019). The standardized regression coefficients were employed to compare the strength of causal relationships in hypotheses (Kwan & Chan, 2011). Hypotheses H1 and H2 were supported, and H1 is comparatively stronger than H2 based on the factor loadings. While technology use positively impacted supply chain and factory smartness, the impact was stronger on factory smartness. Hypotheses H7 to H10 were supported; thus, factory smartness positively impacts all four organizational outcomes. Hypotheses H11 to H14 were also supported, indicating that supply chain smartness positively affects all four measured outcomes. The regression coefficients indicated that supply chain smartness's impact on organizational outcomes is weaker than factory smartness with H3 to H6 recording coefficients greater than 0.5 and H7 to H10 having coefficients less than 0.5. Figure 5.3 illustrates the research results.

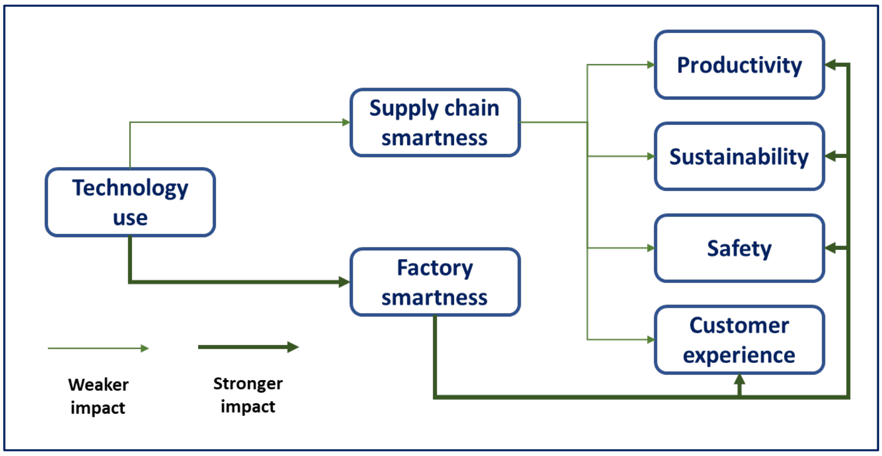

Figure 5-3 - Research results

A comparison of smartness's impacts on outcomes across the factory and supply chain channels based on the standardized regression coefficients in Table 5-8 shows that the strongest impact of factory smartness is on safety and sustainability. In contrast, supply chain smartness has its strongest impact on productivity and sustainability.

5.6 Discussion

The study used the model defined in Figure 5.2 to investigate the value creation in industrial organizations through digital transformation. It examines three points in the digital transformation value process, the point at which technology is embedded in production processes, the point at which technology inputs create the intermediate capability outcome (smartness), and the point of realizing organizational outcome benefits. The results provide clear evidence that technology use in Industrial production creates a sequence of effects that translate to positive organizational performance outcomes. These effects induce smartness in aspects of the production value chain, resulting in performance improvement and confirming the fundamental premise of IDT as a technology-driven value delivery mechanism (Xu et al., 2021).

Smartness is central to IDT. It is the capability created in the production enterprise through digital transformation and the basis of its value creation. The study's results established the value-creation potential of enterprise smartness. First, technology use resulted in smartness

(Hypotheses H1 and H2), and factory transformation, which created more smartness than supply chain transformation, produced significantly better organizational outcomes (Hypotheses H3 to H10). The study conceived a maturity measure based on smartness as the intermediate outcomes measure in an input-output model (Dutta et al., 2005a), in contrast to the popular concept of measuring inputs (Dikhanbayeva et al., 2020). This maturity model built on the measure of smartness reflects, more accurately, the capacity of the digitally transformed production organization, helping establish a more reliable value proposition for IDT.

Analyzing the regression coefficients in Table 5-8 provides a deeper understanding of the results, enabling the comparison of value paths through the factory and the supply chain. The results presented in Figure 5.3 shows that transformation efforts delivered more smartness in the factory than in the supply chain (hypotheses H1 and H2), which delivered better organizational value (H3 – H10). Hypotheses H1 – H10 collectively validate the study's premise that smartness is the basis for value delivery in IDT. A closer look at the data in Table 5-8 provides a deeper understanding of the relative impacts of transforming the factory and the supply chain

The smart factory delivered its strongest impact on Safety. This impact is explained by the higher degree of worker engagement in the factory than in the supply chain. The supply chain could be modeled as a horizontal integration of clusters of production processes and systems (Nagurney, 2009), where direct integration of people is through the systems and processes clusters (factory). The factory transformation also strongly influences sustainability, reflecting the role of optimal resource utilization through smart functionalities in results. The supply chain transformation has its strongest influence on productivity, suggesting that the efficiency gained through applying smartness in logistical processes in production has significant materiality to results. Overall, factory transformation strongly influences all outcomes and should be prioritized in industrial digital transformation.

5.7 Managerial Implications

The value of measurability to management is an established principle (Drucker, 2012; Earll et al., 2000). The study produced a framework for IDT maturity modeling for measuring IDT capability development based on outcome measures rather than effort measures which are common in the literature. An outcome-based model for measuring IDT capabilities presents a more accurate reflection of reality with more practical utility.

Previous studies established that digital transformation programs are overly skewed toward technologies and require repositioning toward business value (Heavin & Power, 2018). This study offers managers an empirically validated path from technology use to business value. The results, a detailed IDT value path, can guide strategies focused on the organization's unique priorities, as in Table 5-9.

Key success factor	**Managerial implications**
Technology use	Managers should focus on the relationship between their use of technology and enterprise smartness. Technology implementation can not be used as a measure of transformation success.
Factory smartness	Managers should focus their IDT effort on production processes and systems (the factory). This is where the most value was created along the value chain. The transformation of the production process delivered organizational outcomes irrespective of the level of smartness in the products being produced.
Supply chain smartness	Supply chain smartness delivered value for all outcome measures. This should be prioritized after factory smartness.
Customer experience	The study established that IDT delivers customer experience goals by transforming the factory and the supply chain. However, there is latitude for more significant customer experience impacts through smart products. According to the study, smart product impacts are not generalizable across industries; managers should consider the opportunities presented by smart products in their specific industries.

Productivity	In addition to the factory, the supply chain transformation delivered strong productivity gains. While the study established that factory transformation should be the priority for IDT, the results also show that supply chain transformation could contribute significantly to productivity. Managers should therefore consider both channels in their strategy.
Sustainability	Sustainability gains are relatively strong for both factory and supply chain transformations. Both thus represent avenues for managers to actualize their strategies depending on their sustainability goals.
Safety	Managers can achieve significant improvement in worker safety by transforming the factory. Safety delivered the most gain comparatively from the smart factory. Factory transformation should be high priority if worker safety is a challenge.

Table 5-9 - Key managerial implications

The study identified differentiation in the value potentials of different aspects of the value chain from digital transformation, providing a deeper context to the IDT narrative of transforming the value chain end-to-end. To optimize transformation investments, managers must consider the differentials in value potentials along the chain when planning transformation programs rather than assume they must transform the entire chain, particularly when resources for transformation are scarce. The factory delivers the most value from digital transformation, followed by the supply chain and the value of products transformation being industry-dependent. The differentials in value potential along the chain create channels within the value path aligned to different organizational priorities, which can help embed unique organizational goals in Industry 4.0 strategy.

5.8 Conclusion

The study advances the IDT narrative that digital transformation of the Industrial production value chain delivers value to shareholders, customers, employees, and the wider society. It established that IDT delivers value by making the production enterprise smart. Specifically, it determined that IDT and the consequent smartness have implications beyond productivity; it strongly impacts sustainability, customer experience, and worker safety. It also established differences in the impacts of digital transformation on different aspects of the value chain, with stronger impacts on outcomes recorded in the factory than in the supply chain.

This study aimed to generate high-level generalizable results. However, industry-specific studies could produce more nuanced knowledge. Such studies could consider the role of smart products in IDT, as many industries do not make products associated with smartness. Future research can also consider outcomes from the lenses of customers and other stakeholders. Further research should also determine the appropriate transformation of industrial business models to realize smart product value.

5.8.1 Limitations and future research directions

The key limitation of this study is trade-off of industry-specific factors for model generalization. Future studies should consider industry specific factors in Industrial digital transformation and performance considerations. Such studies could give in-depth consideration to smart products as a component of enterprise smartness. They could also consider unique contexts for the performance factors in each industry. Future studies should consider industry segment as a moderator in the model relating technology use, smartness and organizational performance.

Nevertheless, this study has made a vital contribution to the value proposition or impact of IDT on organizational value creation.

6 CONCLUSION

6.1 Research overview

Industry 4.0 is the embedding of digital technologies in industrial production processes to enhance production performance. It achieves industrial digital transformation (IDT) through the end-to-end integration of production value chains. Given that industrial production involves physical and virtual elements, the integration of the production value chain is characterized by cyber-physical integration enabled by cyber-physical systems. Dutta et al. (2005a) described capability as the system enablement for translating inputs into outputs. Industry 4.0 transforms the production enterprise into a system that translates technology use into organizational performance gain through smartness as capability (sections 2.3, 2.6, and 5.6). IDT enables smartness through information transparency achieved by integrating the production value chain. However, the application of smartness in practice is hindered by strategizing challenges, including justifying the rationale for the investment (Szalavetz, 2019), appropriately quantifying progress (Haider et al., 2006), identifying the right technologies, tools, and models (Wang & Wang, 2022), and charting the path to value delivery (Machado et al., 2019). This study aimed to help managers in their Industry 4.0 journey by answering the question, “why Industry 4.0?” It developed a conceptual framework to help guide the process and a maturity model for quantifying IDT development. It established empirical relationships between digital transformation maturity and the performance of the production enterprise to determine the value proposition of Industry 4.0 and IDT.

The study leveraged management and information systems literature on systems theory, dynamic capabilities, maturity modeling, and digital transformation to address its objectives. The literature provides the theoretical basis for Industry 4.0 value creation, i.e., Integrating the value chain end-to-end to facilitate holistic production enterprise management that results in smartness. Smartness is a dynamic capability that enables performance enhancement (sections 2.6 and 4.6).

Through four core chapters that report directly from the qualitative and quantitative phases, the research produced empirical evidence of IDT's value proposition by determining the impact of Industry 4.0 maturity on organizational performance. The determination of the IDT's value proposition is built on components developed in the qualitative phase of the research, including the conceptualization of IDT and smartness and identifying the industrial production performance metrics.

This study used a mixed-method approach to achieve its objectives. The approach employed initial qualitative research to determine the measures used in testing during the quantitative research. The qualitative study used semi-structured interviews with experts from top global technology companies. The participants were technology and digital transformation experts. The qualitative phase of the research determined the technology features that support IDT capabilities, the conceptualization and assessment factors for smartness required to facilitate an outcome-based IDT maturity model, and the performance metrics for Industry 4.0 and IDT.

6.2 Results overview

The research produced tools, concepts, and models for IDT consolidated in Figure 6-1 as an integrated framework for IDT (stemming from chapters 2-5). It describes the IDT capability development process, from implementing technologies to delivering organizational value. This framework will be further discussed in this section (specifically sub-sections 6.2.1 – 6.2.5).

The study addressed the challenges of IDT. It identifies the digital transformation tasks undertaken by organizations and presents a framework for addressing the complexity of the transformation endeavor. IDT is established as a technology-based value-creation process with managers using digital technologies to create value for the production organization. The study's framework identifies the technology and value components and establishes their links. It enables managers to navigate the path from technology to organizational value through the digital transformation process.

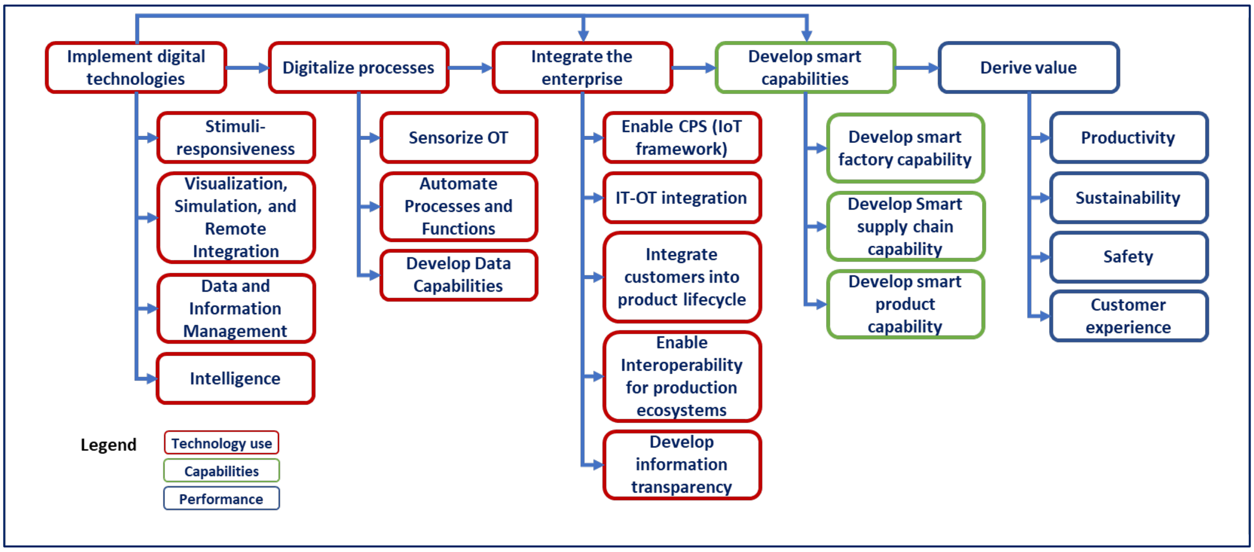

Figure 6-1 - Integrated industrial digital transformation (IDT) framework

6.2.1 Technology

The IDT value creation process is technology driven. It uses technology to create smart functionalities for performance improvement. The value of technology to IDT is thus based on its relevance to smartness. Many technologies have been associated with Industry 4.0, and the list will continue to evolve as new technologies that contribute to Industry 4.0 capabilities emerge. It is advantageous to have a framework with significant technology agnosticism for generalized applicability. The study thus identified four groups of technology features crucial to making the enterprise smart (section 2.5.1):

- Stimuli responsiveness – enabled by sensors and actuators to facilitate environmental interaction and openness.
- Visualization, simulation, and remote access – facilitates flexibility of data and information, including location-based flexibility (ubiquitous access) and time-based flexibility (predictive analytics and extended reality).

- Data and information management – enabled by digital infrastructure, including computing platforms (cloud and edge), enterprise information systems, cyber security, etc. It provides data collection, storage, protection, processing, analysis, and communication functionalities.
- Intelligence – enabled artificial intelligence, machine learning, natural language processing, computer vision, etc., to facilitate knowledge acquisition, reasoning, and problem-solving capabilities.

Important technology implications from this study include:

- Focus on critical smart functionalities. While the significance of technology implementation continues to dictate the notion of digital maturity, smart functionalities are the mechanism through which IDT creates organizational value (sections 2.6 and 4.6). The success of implementations is not an adequate measure of transformation progress. Rather, smartness is an appropriate measure of digital maturity (section 5.7).
- IDT strategy must use technology investments to foster a holistic management approach (section 4.6). The challenge of inadequate investment resources pressures managers to pursue silo and reductionist approaches. They must, however, enable a holistic approach by shortening the cycle between investing and value realization by using a measure of smartness enablement capacity to prioritize acquisition. Priority technologies would digitalize processes, integrate production elements and provide data and information management functionalities (section 2.5.2). Many technologies associated with Industry 4.0 predate it (section 2.6), and valuable technologies would already exist in the enterprise. The ability to reuse and re-purpose existing technologies for cyber-physical systems and enterprise smartness is important.

6.2.2 Digitization

Enabling the information transparency that unpins IDT requires digitizing Information and processes. Digitalizing machines or operating technologies with sensors and industrial processes with autonomous actuators is a defining feature of Industry 4.0 as it enables cyber-physical integration. Digitization's role in IDT relates to data capability. It enables data at both ends of stimuli responsiveness, acquisition, and utilization, facilitating systems' interaction with their environment. Industry 4.0 strategy, therefore, involves digitalizing information and processes to improve the production enterprise's data capability and information transparency.

6.2.3 Integration

Integration is the running theme for Industry 4.0. It connects production elements, including materials, devices, products, processes, systems, and people, enabling the flow of information among them. It is the mechanism by which the production enterprise function as a single entity to facilitate information transparency, smartness, and performance optimization.

Through integration, the production value chain is manageable as a single system. Information transparency is the practical utility derived from integration and the basis for smartness (section 4.5.7). Integration quality is characterized by the completeness, correctness, timeliness, and accessibility of information about production elements in the value chain.

The important integration points are:

- Integration quality is measurable by information transparency which is its practical utility (section 4.5.7)
- Adequacy of technology infrastructure for cyber-physical systems enablement underpins integration capacity.

- Focal firms in the production ecosystems can drive holistic approaches and facilitate long-term benefits realization by promoting the balanced performance metrics identified in this study in the vertical integration arrangements (section 4.6.1).

- Interoperability will replace tight integrations in many aspects of the production enterprise. Practitioners can aid development by driving this design principle (section 2.5.2.4).

6.2.4 Smartness

The study determined that smartness is the organizational capability through which IDT creates value. Understanding and measuring smartness was a key part of the research to facilitate its management, as smartness is identified as the appropriate measure of IDT maturity. The following are key points on smartness from the study:

- Smartness positively correlates with technology use, enterprise integration, and information transparency.
- Flexibility and autonomy are functional attributes of smartness in the Industry 4.0 context. They also serve as measurement parameters.
- While IDT induces smartness across the production value chain and is observed in the factory, the supply chain, and products, factory smartness produces higher organizational value than smartness in other aspects of the value chain.
- The value proposition of product smartness is industry-specific (section 5.6). It is not always necessary for smart factories to produce smart products.

6.2.5 Value derivation

Organizations embark on IDT to create value, optimizing organizational outcomes through smartness derived from integrating the enterprise into a singular functional system (sections 2.5.4 and 4.3). The study identified smartness as the optimization mechanism built on data capabilities and information transparency (section 2.5.4). Organizations must thus ensure that all data related to performance parameters identified in the study are acquired and managed. The parameters identified include product innovation and quality, production cost and efficiency, resource utilization, physical environmental impacts, social value creation, task transformations, and hazard elimination or reduction.

- Long-term value creation is premised on holistic management of the production enterprise, avoiding a reductionist approach.
- Value creation must be balanced, considering all stakeholders through productivity, sustainability, customer experience, and safety.
- While Industry 4.0 proposes an end-to-end digital transformation of the production value chain, aspects of the value chain have differentiated value potentials concerning digital transformation (section 5.6). The factory produces the most value, and opportunities for smart products are industry specific.
- The supply chain transformation presents an opportunity to address specific organizational objectives, particularly productivity and sustainability. A nuanced approach to transforming aspects of the value chain is thus required to maximize investment resources.

6.3 Research contribution

The study made a significant contribution of a digital transformation framework to drive organizational performance. This framework is important for organizations in addressing the challenges of developing transformation strategies optimized for their unique objectives. Unlike prior studies, this study explored the systems perspective of industrial digital transformation as an input-output system with an intermediate capability outcome (smartness). The study contributed a framework that helps chart the path from technology to value delivery. It conceptualized smartness to aid its understanding and enable its development to support an Industry 4.0 maturity model, improve transformation progress measurement through a novel and simple maturity model, and make an empirical determination of the value proposition of industrial digital transformation. Through the above, the study made significant contributions to Industry 4.0 and digital transformation literature. The core contributions are highlighted below:

6.3.1 Industry 4.0 framework

Implementing Industry 4.0 and its research endeavors requires navigating extensive technologies, tools, and concepts. The study contributes conceptual and value frameworks for Industry 4.0 (Figure 2-1, Figure 4-1, and Figure 5-1). It further integrates the models into an Industry 4.0 model that supports the IDT process. It answers the what question, specifying the activities involved in industrial digital transformation and the expected outcomes. The framework helps digital transformation practitioners envision the target state for the transformed organization, supporting the planning for transforming the organization from the current state to the target state and establishing the thread between effort (technology implementation) to outcomes (value creation).

6.3.2 Smartness framework

Smartness is an intermediate outcome of Industry 4.0 that enables the optimization of the integrated production enterprise. Its value proposition is thus tied to the capacity to develop smartness and translate it to production performance gain, necessitating the development of a framework for qualifying and quantifying smartness to progress its development. This study's framework identified the defining characteristics of smartness, its classification, and the functional parameters for evaluating the quality of smartness. The framework enables the application of smartness as the basis for Industry 4.0 maturity modeling.

6.3.3 Industry 4.0 maturity model

Effective management of the transformation process requires measuring the maturity of capabilities to manage the development process and quantify its impact. This study contributes a maturity model designed to address the challenges of model representation of reality and practical usefulness. It does this by focusing the measure of maturity on the level of smartness achieved in the production enterprise rather than technology implementation endeavors. Strategic management literature confirms that there is no linear relationship between the stock of valuable technology assets and useful capabilities (Teece & Pisano, 2003). Measuring capabilities thus represents a more accurate measure of the utility of digital transformation than technology implementation efforts. The model builds on smartness as the intermediate outcome of integrating digital technologies in production processes. The model evaluates three factors (technology use, production process smartness, and supply chain smartness), as illustrated in Table 5-1. It evaluates enterprise smartness by considering the flexibility and autonomy of the factory and the supply chain. The model also has an effort component that measures technology use as an organizational capability to provide an effort component for understanding maturity. Technology use is an organizational capability that encapsulates technical and managerial requirements. It evaluates the embeddedness of sensors, actuators, digital infrastructure, artificial intelligence, and extended reality in the production process.

6.3.4 Industry 4.0 value proposition

The general narrative of Industry 4.0 is to transform the production value chain through digitization and integration end to end. The study identified that the contribution of Industry 4.0 is beyond shareholders' financial performance interests but applies to stakeholders' broad interests, impacting productivity, sustainability, employee safety, and customer experience. The study also identified that the expression of smartness across the value chain, including in the production processes and systems and in the supply chain, delivers different profiles of performance gains. The study produced nuanced relationships between enterprise smartness and organizational outcomes, enabling practitioners to design transformation strategies that address their specific objectives.

6.4 Managerial Implications

Managerial challenges of digital transformation include justifying the investment through establishing a value proposition, quantifying digital transformation progress, and navigating the complex digital transformation landscape to deliver a plan that addresses organizational goals and challenges. The study produced an Industry 4.0 framework (Figure 6-1), incorporating a business capability model () and an Industry 4.0 conceptual framework (Figure 2-1). It enables managers to establish a logical thread from their technology initiatives to organizational value realization, highlighting organizational features that represent key landmarks in the transformation journey.

Maturity measurement is critical to managing capability development. Managers need the ability to graduate maturity levels according to business priorities. Due to their predominantly effort measure base, existing Industry 4.0 maturity models remain limited in assisting with Industry 4.0 strategy and investment decisions. This study contributes a maturity model that integrates outcome measures based on a novel smartness framework, enabling maturity evaluation based on capabilities material to performance, having discounted the dissipated portions of the input. The Industry 4.0 maturity model contributes to theory and practice. The conceptual framework for smart systems that facilitated the outcome measures could also be useful for managing smartness in contexts other than Industry 4.0, as increasing data capabilities, machine intelligence, and stimuli-responsiveness infrastructure create opportunities to exploit smartness in many contexts.

The study's differentiation of aspects of the value chain provides insights into the existence of multiple value paths for digital transformation within the chain. These insights offer a deeper context to understanding Industry 4.0 as an end-to-end value chain transformation. Considering the potential for transformation to involve complex global value chains, managers can leverage the differences in value potentials along the value chain to optimize their strategy, especially regarding the allocation of digital transformation resources.

Competition for scarce investment resources will pressure managers to pursue short-term reductionist approaches. Respondents in the qualitative phase argued that "*the level of investment required to drive it to fruition will be difficult to achieve at this point*". Investments must be initially channelled to aspects of the value chain that contributed more to smartness and those that delivered the quickest. For example, the automotive industry started its digital transformation journey with factory autonomous functionalities before progressing to address smartness opportunities in the supply chain and products (Lee et al., 2023). Factory smartness delivered business gains through production efficiencies and product quality, enabling investments in more sustainable and feature-rich supply chains and products in subsequent investment cycles. The study provides them with practical strategic levers for avoiding expensive and potentially risky ill-conceived approaches to value chain transformation.

Managerial implications offered by this study include:

- ***Technology use*** - Managers should ensure the adequacy of technology embedding in the production processes driven by organizational objectives. The focus here should not be the acquisition and implementation of technologies but the delivery of fit-for-purpose technology as a service for business consumption incorporating the technical and management components of technology service delivery.

- ***Integration*** – Managers should ensure connectivity and participation of all production entities, including people (employees and customers), devices, systems, materials, products, and organizations in the production information network. The measure of integration must be information transparency – the correctness, completeness, timeliness, and accessibility of all relevant information about all production elements. Furthermore, the study identified IT-OT integration as an underpinning structure for the end-to-end value chain integration and a running theme for Industry 4.0. IT and

OT are historically siloed structures, representing separate people organizations, business processes, systems, and thought processes. Technology alone will not achieve the needed integration. To facilitate this integration, managers must devise organizational structures, management frameworks, and culture change programs. For instance, agile methodologies in project organizations have been identified as helpful in breaking existing silo walls between IT and business units (Colavita, 2016).

- ***Data capability*** – The study established that "*Data is an important part of the Industry 4.0 idea; it is the lifeblood of Industry 4.0*". Therefore, executing the Industry 4.0 paradigm implies that production organizations must uplift their data capability. Managers must ensure that key aspects of data capability, including data asset capture, governance, and utilization for developing autonomous functionalities and improved decision-making. Furthermore, the study identified information transparency, the ubiquitous availability of contextual information on all aspects of production, as central functionality to Industry 4.0 value creation. Developing the organizational data capability involves technology implementation, new management processes, and culture change. Managers must ensure that data capability uplift is well-resourced and driven with senior leadership support for Industry 4.0 success.
- ***Smartness*** – Managers should focus their digital transformation effort on developing enterprise smartness. Smartness rather than technology implementations is the appropriate indicator of Industry 4.0 maturity. Significant attention should be put on delivering the smart factory in the digital transformation strategy because it strongly impacts outcomes. A smart supply chain and smart products can deliver specific aspects of strategy where applicable.
- ***Customer experience*** - Industry 4.0 improves customer experience across the board due to product quality improvements. However, managers should explore the

possibility of more significant benefits from product smartness and mass product customization. Product transformation through smartness is a core part of the Industry 4.0 value creation process. It leverages persistent customer integration to connect products' production and operations contexts into a cyclic lifecycle. Managers must facilitate the product lifecycle transformation through enhanced customer and product lifecycle management functionalities. This typically involves implementing better customer relationship management (CRM) and project lifecycle management (PLM) systems. It also involves developing better processes and aligning organizational structures to support the new product lifecycle paradigm. Managers should consider the unique smart product opportunities that Industry 4.0 presents for their industries in crafting their strategy.

- ***Value realization*** – The capability maturity model integration proposes quantitative management of capabilities. The study identified several important factors across the four performance metrics. Factors relevant to organizational objectives should be managed quantitatively to deliver Industry 4.0 benefits. Some of the factors identified in the study include work tasks automation, process automation, resource utilization, product lifecycle integration, product innovation, product quality, partner interoperability, supply chain coordination and optimization, customer integration, production batch size flexibility, environmental impact, social value creation, hazard reduction, and technology safety features.

6.5 Policy implications

The study's outcomes identified the impact of Industry 4.0 on factors with relevance beyond the production organization. These factors include employment, equality and social justice, sovereign manufacturing capability, environmental sustainability, transnational integration, and economic growth (2.5.3 and 4.5). Industry 4.0 is thus a significant concern for policy makers.

- The study identified that funding is an initial challenge for Industry 4.0 and investment strategies must employ a nuanced approach in allocation resources to aspects with strong and quick impacts (4.6.1). Public investments in digital transformation should employ this same approach given the size of public spending and its potential impact.
- The study recognized the development of specific technological and organizational features as key for actualizing the vision of Industry 4.0 (2.5.1 and 2.5.2). Public investments in research and development must include a strategic focus on these features.

6.6 Limitations and Future Research

This study highlights the complexity of the industrial digital transformation endeavor. While it answers important questions that justify investments in Industry 4.0, other questions come to the fore.

First, this study has considered Industry 4.0 value proposition and strategy at the organizational level. However, given the role of governments and the global nature of modern production value chains, it will be helpful for future research endeavors to pursue answers to the specific details of value propositions of Industry 4.0 at the national and global levels with empirical foundations.

This study explored the role of technology use in the emergence of smartness in industrial production and the role of smartness in performance improvement. An exploration of smartness as a mediating factor in industrial production performance improvement induced by digital transformation would help generate a more rounded understanding of the role of smartness in industrial production.

While this study has derived relevant measures of value that include customer experience, employee safety, and sustainability, the value was viewed from the firm's perspective. Other studies should consider the value proposition from the specific lenses of different stakeholders to generate a holistic view of value.

This study considered production organizations broadly to produce generalizable results. However, industry-specific insights would also be useful. Future studies should consider the industry-specific value proposition of Industry 4.0. They could also provide further value to practitioners and managers by considering the impact of organizational factors, including firm size and complexity, on Industry 4.0’s value proposition.

Nevertheless, the study makes a valuable theoretical and practical contribution in providing a digital transformation model for production performance to assist organizations in advancing their industry 4.0 journey.

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APPENDICES

Appendix A – Information Sheet for Qualitative Research

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CRICOS Provider No. 00114A

INFORMATION SHEET
for *Interviews*

Title: Diffusion of Innovative Manufacturing Technologies in the Manufacturing Sector

Researchers:

Temitayo Abiodun
College of Science and Engineering
Flinders University
Tel: +61 8 8201 2243

Description of the study

Industry 4.0 is the phenomenon that characterises the fourth industrial revolution. In a manufacturing context, it involves the massive deployment of advanced digital technologies like data analytics, robotics, and automated guided vehicles (AGVs).

This project will investigate the factors that affect the adoption Industry 4.0 capabilities by manufacturing organisations. It will also consider the contribution of these technologies to business goals and factors that affect the successful implementation of digital technologies.

Purpose of the study

Industry 4.0 has become a very important part of the strategy of manufacturing organisations, it has also become a key strategy for increasing manufacturing output and achieving sovereign manufacturing capabilities in many countries. Furthermore, the Industry 4.0 technology landscape is quite complex and fast evolving, this study proposes to develop knowledge that provide guidance to organisations about their Industry 4.0 requirements and the available paths for the evolution of their capabilities.

What will I be asked to do?

You are invited to attend a one-on-one interview with a researcher who will ask you a few questions regarding your views about your:

- Industry 4.0 and Industrial digital transformation
- Your experiences about the drivers of innovation and project success in organisations
- Your views on the impact of specific technologies on business outcomes
- Your experience with Industry 4.0 implementation projects.

Participation is entirely voluntary, and you may withdraw at any stage without disadvantage to your relationship with Flinders University and its staff and students. The interview will take about 45 minutes and will be conducted by video conference (Microsoft teams, Zoom or Skype) at a time that is convenient for you.

With your consent, the interview will be video recorded on the videoconferencing platform to help with reviewing the results. Once recorded, the interview will be transcribed (typed-up) and stored as a computer file. The video recording will be deleted after transcription.

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With your consent, the interview will be video recorded on the videoconferencing platform to help with reviewing the results. Once recorded, the interview will be transcribed (typed-up) and stored as a computer file. The video recording will be deleted after transcription.

Appendix B - Semi-structured interview guide

- What is Industrial Digital Transformation (including Industry 4.0, Industrial Internet of Things (IIoT), and Industrial Internet)?
- Which technologies are important for IDT and why?
- Which management competencies are important for IDT and why?
- Which business factors have driven the adoption of IDT capabilities? (productivity, safety, etc.)
- Which business factors have hindered the adoption of IDT technologies? (Cost, complexity, etc.)
- What role do environmental factors play in the adoption of these technologies? (Competition, Regulation, etc.)
- What role do organizational factors play in the adoption of these technologies? (Size, complexity)
- What role do technological factors play in the adoption of these technologies? (Exiting technology investments, implementation, integration, management capabilities, etc.)
- How does IDT influence organizational performance?
- What is smartness, and how is it related to IDT?

Appendix C – Information Sheet for Quantitative Research

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CRICOS Provider No. 00114A

INFORMATION SHEET
for *Survey*

Title: Diffusion of Innovative Manufacturing Technologies in the Manufacturing Sector

Researchers:

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Description of the study
Industry 4.0 is the phenomenon that characterises the fourth industrial revolution. It involves the massive deployment of advanced digital technologies like robotics and automated guided vehicles (AGVs) in manufacturing processes. This project will investigate the factors that affect the adoption of advanced digital technologies in Manufacturing processes. Adoption of digital technologies and the attendant digital transformation is important for the future success of the manufacturing industry.

Purpose of the study
The project focuses on identifying the key factors in the adoption of Industry 4.0 technologies in manufacturing, with the goal of promoting the uptake and diffusion of technologies within manufacturers and their supply chains.

What will I be asked to do?
You will be asked to complete an online survey that should take about 20 minutes. Most of the survey questions involve rating scales where you will be asked to indicate the extent to which you agree or disagree with a statement related to advanced technology adoption. Participation is entirely voluntary, and you may withdraw at any stage without explanation. If you agree to participate, click the link provided in the box above.

What benefit will I gain from being involved in this study?
Your input will help shape future work practices in manufacturing firms, potentially improving firm innovativeness and other business outcomes. There are also potential economic outcomes for the nation.

Will I be identifiable by being involved in this study?
A generic link to the survey will be used so neither the researcher nor organisation will know which employees have participated (i.e. your participation is anonymous). No individual responses will be identifiable.

Appendix D – Quantitative Questionnaire

1. What country are you responding from?
2. My work mainly relates to the following industry:
    a. Automotive
    b. Chemicals
    c. Electronics
    d. Food and Beverages
    e. Heavy equipment
    f. Household goods
    g. Metals and Plastics
    h. Others
    i. Pharmaceuticals
3. What is your level of understanding of the term "Industry 4.0"?
    a. None
    b. Little
    c. Average
    d. Good
    e. Excellent
4. How many employees are in your company?
    a. 1 – 10
    b. 11 – 100
    c. 101 – 1000
    d. 1001 – 5000
    e. Greater than 5000

The next set of questions evaluates organizational capability based on the Capability Maturity Model Integration (CMMI) Framework. The response options are below:

Initial - The processes exist, but performance is ad hoc.

Managed - Processes are governed at a sub-enterprise level. There is a lack of coordination for similar processes across the enterprise.

Defined - Processes are standardized across the enterprise against best practices, enabling consistency enterprise-wide. The operations of processes are governed and documented.

Quantitatively managed - Process performance is controlled using statistical methods. Performance at this level is predictable, and there focus on managing deviations.

Optimizing – Processes have continuous improvement measures built on quantitative measures.

5. What is the CMMI level for the use of ***Sensors (Sensors, IoT, Embedded devices, RFID etc)*** in your organization?
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing
6. What is the CMMI level for the use of Robotics (Digital fabrication, cobots, Industrial robots, Automatic Guided Vehicles (AGVs) etc) in your organization?
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing

7. What is the CMMI level for the use of Extended Reality (Virtual / Augmented reality, Digital twins, Live-Virtual Construct (LVC), Simulations etc) in your organization?
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing
8. What is the CMMI level for the use of Digital Infrastructure (Cloud / Edge Computing, broadband & NXG networks, Cyber security etc) in your organization?
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing
9. What is the CMMI level for the use of Artificial Intelligence (Machine learning, Natural Language Processing, Predictive analytics etc) in your organization?
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing
10. What is the CMMI level for ***Process autonomy*** e.g., processes do not need human intervention, including for decision-making?
    a. Initial
    b. Managed
    c. Defined

d. Quantitatively managed
e. Optimizing

11. What is the CMMI level for ***Process flexibility*** e.g., production processes can be changed e.g., to produce new products or change specifications of existing products, without building new factories or installing significant new machinery
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing
12. What is the CMMI level for ***Supply chain autonomy*** e.g., Dynamic, intelligent handling of demand (routing, resource allocation) along the supply chain?
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing
13. What is the CMMI level for ***Supply chain flexibility*** e.g., automated handling of disruption and demand changes along the supply chain?
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing

14. What is the CMMI level for ***Product autonomy*** e.g. automation of product lifecycle management? Products can be maintained and supported without human intervention.
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing
15. What is the CMMI level for ***Product flexibility*** e.g. products are highly configurable and customizable for customers in an automated fashion?
    a. Initial
    b. Managed
    c. Defined
    d. Quantitatively managed
    e. Optimizing

The next set of questions measures your perception of organizational performance

16. Our production processes and systems are effective (they get the job done)
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree
17. Our production processes are efficient (they utilize resources well)
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree

d. Somewhat agree

e. Strongly agree

18. Our product quality is better than competitors

    a. Strongly disagree

    b. Somewhat disagree

    c. Neither agree nor disagree

    d. Somewhat agree

    e. Strongly agree

19. Our safety incidence record is better than our peers’

    a. Strongly disagree

    b. Somewhat disagree

    c. Neither agree nor disagree

    d. Somewhat agree

    e. Strongly agree

20. Our safety process has senior leadership engagement

    a. Strongly disagree

    b. Somewhat disagree

    c. Neither agree nor disagree

    d. Somewhat agree

    e. Strongly agree

21. Our customers are satisfied with our products and services

    a. Strongly disagree

    b. Somewhat disagree

    c. Neither agree nor disagree

    d. Somewhat agree

    e. Strongly agree

22. Our customers recommend us to others
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree
23. Our customers are generally loyal to us
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree
24. Our company is effective at optimizing resource use (energy, water, and materials)
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree
25. Our company is effective at minimizing our environmental pollution, including Carbon Dioxide emissions
    a. Strongly disagree
    b. Somewhat disagree
    c. Neither agree nor disagree
    d. Somewhat agree
    e. Strongly agree
26. Our company is ethical. We are committed to social good.

a. Strongly disagree

b. Somewhat disagree

c. Neither agree nor disagree

d. Somewhat agree

e. Strongly agree

This is the end of the survey, thanks for participating.

Appendix E – Participant profiles

Respondent	Location	Experience (Years)	Education	Principal Industry Expertise
1	Australia	29	BA	Government, Natural Resource
2	Australia	30	BA	Government, Natural Resource
3	Australia	28	M.Sc	Aerospace
4	Australia	33	B.Sc	Industrial, Utilities
5	France	34	B.Eng	Industrial
6	USA	31	MBA	Automotive
7	USA	35	MBA	Utility, Natural Resources
8	Australia	20	M.Sc	Exploration
9	USA	23	B.Eng	Automotive
10	USA	27	PhD	Industrial, Supply Chain
11	USA	25	MA	Industrial, Supply Chain
12	USA	21	MBA	Industrials, Automotive, Pharmaceuticals
13	USA	25	BA	Industrial
14	Australia	25	B.Eng	Industrial
15	Singapore	36	B.Com	Government, Healthcare
16	USA	29	B.Sc	Technology, Media, Telecommunications

Appendix F – What is Industry 4.0? Responses and First-order concepts

Respondent	Response	First-order concepts
1	The next evolutionary step in production. It is primarily about manufacturing. It has emerged as a confluence of increasing maturity of several systems facilitating interoperability at speed (hyperconnectivity). Industry 4.0 will move the focus in the value chain towards interoperability and away from tight integrations as more agile production ecosystems emerge. We will experience the classic hype cycle effect. The level of investment required to drive it to fruition will be difficult to achieve at this point. It will improve manufacturing in first-world countries because of lower cost manufacturing. It will push the pursuit of more sustainable supply chain arrangement, away from the constant pursuit of lower costs.	Emergence (System of Systems), Hyperconnectivity, Manufacturing cost optimization, Nextgen Communication, Sovereign Manufacturing Capability, Interoperability, Sustainable supply chain
2	Industry 4.0 emerged as a systemic response to fundamental challenges facing production enterprises because of evolving socio-economic realities over a period. First is the increasing demand to customize or individualize products and services to satisfy the changing needs of consumers. The second is the evolving challenge of energy and resource utilization in response to environmental requirements. The third is the volatility of production parameters requiring a higher capacity for flexibility in production enterprises. Industry 4.0 uses smart solutions to address the challenges. Through smartness, Industry 4.0 addresses the challenges that necessitated it. It enables mass product customization, simultaneously delivering value to the producer and consumer as productivity and superior customer experience. It optimizes resource utilization and environmental interaction of production systems. Production systems improve productivity by optimally responding to variability across the production ecosystem	Flexibility, Mass Product Customization, socio-economic value creation, Smart solutions, Resource optimization, Production factors variability, Environmental impact

3	A period of rapid technological advancement with an impact on manufacturing. Both in the contexts of products and platforms. It is revolutionary, resulting in efficiency and effectiveness gains through cps. The previous revolutions had pockets of gains in automation and computing It is the first industrial revolution to go outside the core manufacturing processes. Its impact extends to maintenance, onboard platforms like ships, and resource environments. Development in cybersecurity and extended reality suggests that removal of environmental boundary constraints is key to Industry 4.0 and might define its evolution into Industry 4.1 or even 5.0. This significant provision implies that you do not have to be in the environment to interact with it. Industry 4.0 increases productivity, product and process quality, cost optimization, product innovation, and employee safety. I have personally witnessed a worker's life saved by Industry 4.0 technology when a "man down" technology raised an alarm	Emergence (System of Systems), Enhanced Manufacturing capabilities, Extended reality, Holistic Enterprise transformation, Process Efficiency, Boundary removal, Worker safety, Process quality, Product quality
4	Industry 4.0 is the extension of digitalization principles from IT to OT. IT has long transformed the business technology space of the enterprise. Now the OT space is being similarly transformed and integrated, creating a single digital enterprise. This transformation is dependent on advanced technologies, particularly sensors, robotics, virtual reality, and artificial intelligence. The creation of a singular digital enterprise has profound implication for product development and management. Digital twins play an important role as a critical application of extended reality. Integration does not just happen within the production organization; it transcends the entire production value chain spanning suppliers, consumers, and producers.	Artificial intelligence, Connected enterprise, Data acquisition, Extended reality, Integrated value chain, OT (Operating technologies) Digitization, OT-IT Integration, Robotics, Sensors, Digital twins

5	Industry 4.0 is a set of capabilities acquired by manufacturing enterprises by implementing four classes of technologies. The technologies are computing and networking, human-machine interaction, AI and analytics, and digital fabrication. The implementation of these technologies enable the integration of the value chain and the factory elements resulting in three capabilities, smart products, smart factory, and smart supply chain	Artificial intelligence, Computing infrastructure, Data analytics, Digital fabrication, Integrated value chain, Man-machine collaboration, Smart product, Smart production and supply chain processes, Smart supply chain, Smart factory
6	An Industrial revolution. Taking advantage of advanced technologies, particularly IoT and corporate information systems, to create manufacturing systems, and engineering and product development solutions that are interconnected, communicate, and analyze to drive intelligent actions. The basic business value is customer, the ability to anticipate customer needs and deliver them rapidly.	Connectivity, Integrated systems and processes, Intelligent actions, IoT, New customer experience capabilities, Rapid delivery of customer requirements
7	Industry 4.0 is a series of layered capabilities that deliver optimal socio-economic outcomes in industrial production The layered capabilities are facilitated by advanced technologies that enable stimuli responsiveness, artificial intelligence, data processing, visualization, and robotic actuation.	Artificial intelligence, Cloud computing, Data processing, Digitization, Edge computing, Emergence (System of Systems), Information and data transparency, Integrated systems and processes, Optimal socio-economic value, Robotics, Smartness, Stimuli responsiveness

8	Industry 4.0 is the digitization and integration of the entire production enterprise to deliver an end to end digital value chain. An important factor is the rising customer expectation of mass manufactured customized products. Producers also need to produce the mass customized products at a cost-effective price. Industry 4.0 integrates the entire value chain and enables the engagement of the customer early in the process and throughout the process including after sales. IoT is critical to digitization and integration	Cost-effectiveness, Digital enterprise, Digitization, Integrated value chain, IoT, Mass Product Customization, Persistent customer engagement
9	Industry 4.0 is about integrating the physical and virtual worlds for the purpose of production processes advancement. It is based on a number of key a concept including digitization, seamless man-machine collaboration and universal visibility and accessibility of data and processes. In the Industry 4.0 context, production systems can attain super efficiency, flexible and have information transparency.	Cobots, Digitization, Information and data transparency, Man-machine collaboration, Physical-virtual integration, Process Efficiency, Process Flexibility,
10	Fusion of IT and OT, or the digital and physical components of production (with IoT) to create new socio-economic values. The third industrial revolution created the capability for pulling information from the physical space into the digital. The fourth revolution completes the digital-physical loop by feeding back analyzed information into the physical space from the digital.	Optimal socio-economic value, OT (Operating technologies) digitization, Physical-virtual information loop
11	Industry 4.0 is the digitization of all aspects of production processes, the vertical integration of the factory, and horizontal integration of the production ecosystem with IoT, Enterprise Information Systems and autonomous functionalities. The digitization provides the platform for the integration, while the integration creates the capability for smart characteristics. The horizontal integration connects the entire value chain from suppliers to the consumers while the vertical integration connects the processes within the production enterprise. Data is an important part of the Industry 4.0 idea, it is the lifeblood of Industry 4.0. Data related to all aspects of the production enterprise operations covering planning, production and maintenance are made	Artificial intelligence, Data Analytics, Data Capability, Data processing, Enterprise Information Systems, Information and data transparency, Integrated production enterprise, IoT, Process digitization, Production ecosystems, Real-time business intelligence, Smart

	available in real-time, powering analytics and providing the intelligence required for smart operations.	operations, Vertical integration
12	Industry 4.0 is the next iteration of the series of industrial revolutions that defines how industrial production works. This one integrates technologies often associated with smart capabilities with production , product development and operation systems and processes. It creates a production enterprise that is fundamentally digital and interconnected. It exhibits autonomous functionalities and seamlessly funnels data and analysed information back and forth between the digital and the physical elements to enable further intelligent actions in the physical world. Industry 4.0 ultimately transforms the enterprise into a smart one composed of other smart entities including systems and processes. The essence and impact of Industry 4.0 goes beyond production. It transforms production organization and the entire lifecycle of products. The organizational transformation infuses smartness into the operations of the firm through the appropriation of the value of data. It also transforms the way products are designed, made, used, and maintained. Additionally, Industry 4.0 business models seek to commercially exploit data.	Autonomy, Connected enterprise, Digital enterprise, Enhanced Operating and production processes, Intelligent actions, Physical-virtual information loop, Product development capability, Product lifecycle integration, Smart capability technologies, Smart factory, Smart supply chain, Smart product, Smart processes, Value of data

13	Industry 4.0 happens when several developments in technology are considered collectively rather than individually. These technologies include robotics and AI, digital fabrication, mobile communications, extended reality, and data analytics. Collectively, they create the capability to integrate physical and virtual worlds. The integration further transforms production capabilities bringing speed, transparency, visibility, autonomy and flexibility.	Artificial intelligence, Autonomy, Data analytics, Emergence (System of Systems), Extended reality, Flexible production systems, Information and data transparency, Physical virtual integration, Process Efficiency, Production capability transformation, Robotics, Visibility
14	Applying new technologies including ML, AI, IoT, edge computing, some of which had been applied previously in enterprise business systems contexts, but now to machine and engineering shopfloor contexts. Taking advantage of advancements in sensors particularly, but also computing, cloud and security to change the way machines are run in production, operations and maintenance modes. Industry 4.0 incorporates additional contextual data to enrich the functionalities of existing automation technologies. Industry 4.0 actualizes the cloud factory concept which democratises production infrastructure in the same way cloud computing does for digital infrastructure.	Artificial intelligence, Autonomy, Cloud computing, Cloud factory, Data acquisition, Data Capability, Digitization of Shopfloor processes, Edge computing, IoT, Machine Learning, Sensors
15	Industry 4.0 uses the connectedness of systems and processes across the entire production value chain to create an intelligent, flexible production ecosystem, delivering superior value compared to the unintegrated enterprise. The value created by the integrated intelligent systems include organizational and occupational safety and productivity.	Flexible production systems, Integrated systems and processes, Integrated value chain, Production ecosystems, Smart production systems, Superior value realization, Occupational safety

16	Industry 4.0 is about the creation of fully connected production value chains. The idea thus is to better the capabilities of linear value chain constructs. The new capabilities are based on technologies that provide AI, high throughput and low latency communications and live virtual construct. Producers have both visibility of and dynamic insights on their own operations end to end, covering supply chain, customers and production systems and processes. They have flexibility that enables response in a timely fashion to fluctuations and variability in the operating environment including customer behaviours and preferences, supply chain characteristics, and social, political and economic factors with impact on production.	Artificial intelligence, Flexibility, Improved production capabilities, Information and data transparency, Integrated value chain, Live virtual construct, Nextgen Communication, Persistent customer engagement, Smart supply chain, Visibility

Appendix G – Data Structure

First-order concepts	**Second-Order concepts**	**Aggregate Dimensions**
Artificial intelligence	Digital Technology	Digital Technology
Autonomy	Resource and Process Optimization	Productivity
		Sustainability
Cloud computing	Digital Technology	Digital Technology
Cloud factory	Economic transformation	Productivity
	Smart factory	Capability
	Social value creation	Sustainability
Cobots	Digital Technology	Digital Technology
Computing infrastructure	Digital Technology	Digital Technology
Connected enterprise	Supply chain optimization / Interoperability	Productivity
Connectivity	Resource and Process Optimization	Productivity
Cost-effectiveness	Economic transformation	Productivity
Data acquisition	Data Capability	Capability
Data Analytics	Data Capability	Capability
Data Capability	Data Capability	Capability
Data processing	Data Capability	Capability
Digital Enterprise	Supply chain optimization / Interoperability	Productivity
Digital Fabrication	Resource and Process Optimization	Productivity
Digitization	Resource and Process Optimization	Productivity
Digitization of Shopfloor processes	Resource and Process Optimization	Productivity
Edge computing	Digital Technology	Digital Technology
Emergence (System of Systems)	Supply chain optimization / Interoperability	Productivity

Enhanced Manufacturing capabilities	Resource and Process Optimization	Productivity
Enhanced Operating and production processes	Resource and Process Optimization	Productivity
	Task transformation	Safety
Enterprise Information Systems	Supply chain optimization / Interoperability	Productivity
Extended reality	Digital Technology	Digital Technology
Flexibility	Resource and Process Optimization	Productivity
Flexible production systems	Resource and Process Optimization	Productivity
		Sustainability
Holistic Enterprise transformation	Supply chain optimization / Interoperability	Productivity
Hyperconnectivity	Resource and Process Optimization	Productivity
Improved production capabilities	Resource and Process Optimization	Productivity
Information and data transparency	Data Capability	Capability
Integrated production enterprise	Supply chain optimization / Interoperability	Productivity
Integrated systems and processes	Resource and Process Optimization	Productivity
Integrated value chain	Supply chain optimization / Interoperability	Productivity
Intelligent actions	Resource and Process Optimization	Productivity
		Sustainability
IoT	Digital Technology	Digital Technology
Live virtual construct	Digital Technology	Digital Technology
Machine Learning	Digital Technology	Digital Technology
Man-machine collaboration	Task transformation	Productivity
		Safety
Manufacturing cost optimization	Economic transformation	Productivity
Mass Product Customization	Mass Product Customization	Customer experience
	Product lifecycle transformation	Productivity
New customer experience capabilities	Product lifecycle transformation	Customer experience
Nextgen Communication	Digital Technology	Digital Technology
Optimal socio-economic value	Economic transformation	Productivity
		Sustainability
	Social value creation	Sustainability
OT (Operating technologies) Digitization	Resource and Process Optimization	Productivity
OT-IT Integration	Resource and Process Optimization	Productivity
Persistent customer engagement	Customer engagement	Customer experience
Physical virtual information loop	Data Capability	Capability
Physical virtual integration	Supply chain optimization / Interoperability	Productivity
Process digitization	Resource and Process Optimization	Productivity
Process Efficiency	Resource and Process Optimization	Productivity
Process Flexibility	Resource and Process Optimization	Productivity
		Sustainability
Product development capability	Product lifecycle transformation	Customer experience
		Productivity
Product lifecycle integration	Resource and Process Optimization	Productivity

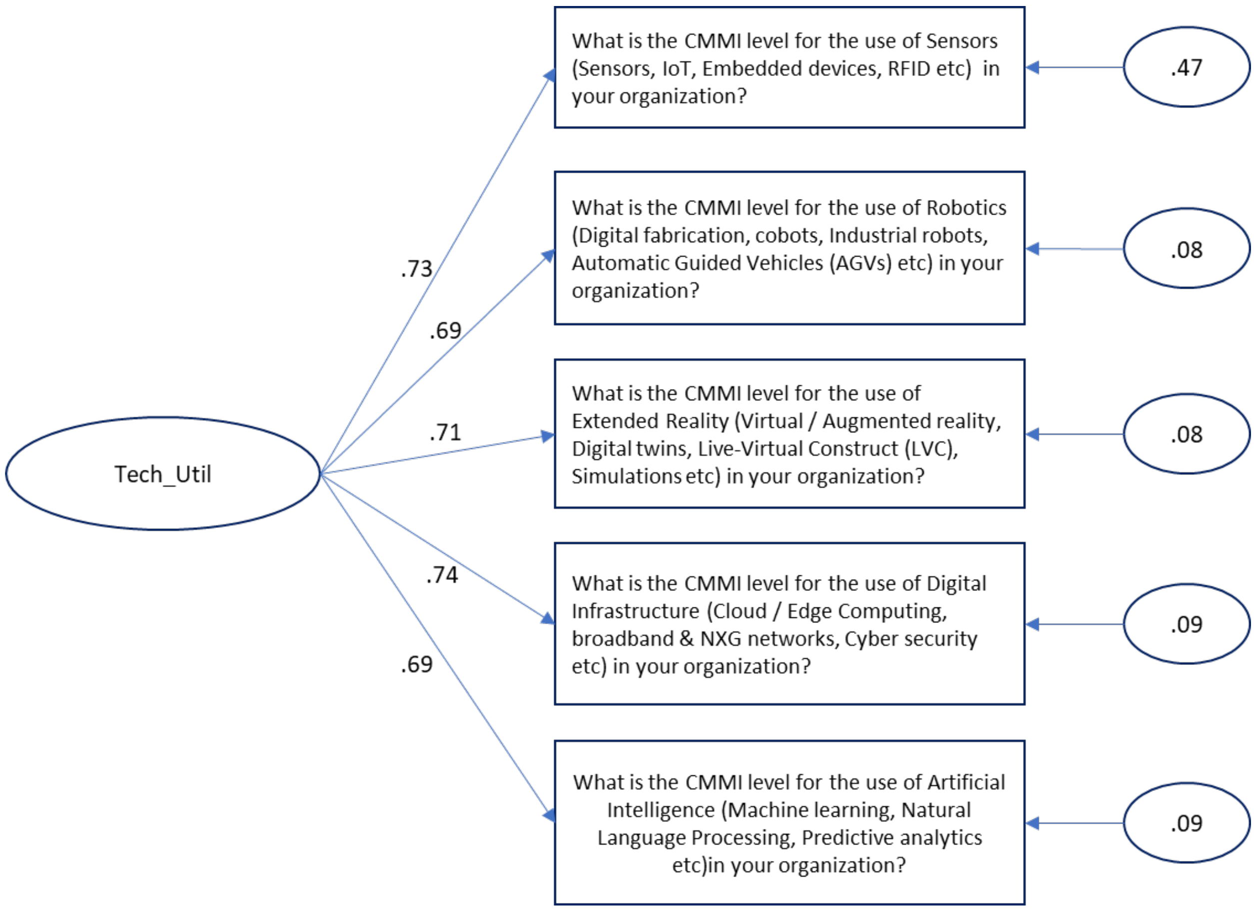
Production capability transformation	Resource and Process Optimization	Productivity
	Task transformation	Safety
Production ecosystems	Supply chain optimization / Interoperability	Productivity
Rapid delivery of customer requirements	Product lifecycle transformation	Customer experience
		Productivity
Real-time business intelligence	Data Capability	Capability
Boundary removal	Resource and Process Optimization	Productivity
Robotics	Digital Technology	Digital Technology
Sensors	Digital Technology	Digital Technology
Smart capability technologies	Resource and Process Optimization	Productivity
		Sustainability
	Technology features	Safety
Smart enterprise	Resource and Process Optimization	Productivity
Smart factory	Smart factory	Capability
Smart operations	Resource and Process Optimization	Productivity
		Sustainability
Smart processes	Resource and Process Optimization	Productivity
		Sustainability
Smart product	Product lifecycle transformation	Customer experience
		Productivity
	Smart product	Capability
Smart production and supply chain processes	Resource and Process Optimization	Productivity
		Sustainability
Smart production systems	Resource and Process Optimization	Productivity
		Sustainability
Smart solutions	Resource and Process Optimization	Productivity
		Sustainability
	Technology features	Safety
Smart supply chain	Smart supply chain	Capability
Smartness	Resource and Process Optimization	Productivity
		Sustainability
Sovereign Manufacturing Capability	Economic transformation	Productivity
		Sustainability
Stimuli responsiveness	Resource and Process Optimization	Productivity
		Sustainability
	Technology features	Safety
Superior value realization	Economic transformation	Productivity
		Sustainability
Value of data	Economic transformation	Productivity
		Sustainability
Vertical integration	Supply chain optimization / Interoperability	Productivity
Visibility	Resource and Process Optimization	Productivity

Appendix H – Assessment of Normality

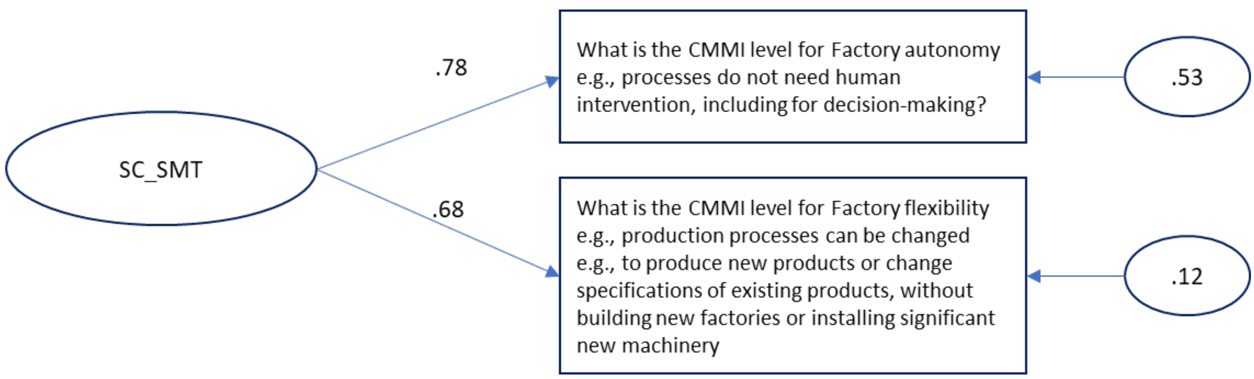
	Item	Skewness	Kurtosis	Bartlett's test of sphericity
tech_util	QT_1	0.084	3.487	0.92
	QT_2	-0.149	3.623	0.91
	QT_3	-0.046	3.684	0.91
	QT_4	0.233	2.848	0.94
	QT_5	-0.155	3.206	0.92
SC_SMT	QS_1a	0.256	3.013	0.91
	QS_1b	-0.019	2.739	0.9
Factory_SMT	QS_2a	0.325	3.098	0.97
	QS_2b	0.122	2.869	0.96
Productivity	QP_1a	-0.048	2.544	0.96
	QP_1b	0.052	2.948	0.95
	QP_1c	-0.154	2.497	0.96
Safety	QP_2a	0.056	3.056	0.96
	QP_2b	0.057	2.869	0.97
Customer	QP_3a	0.340	2.701	0.94
	QP_3b	-0.082	3.163	0.91
	QP_3c	-0.069	3.070	0.9
Sustainability	QP_4a	0.037	2.941	0.98
	QP_4b	0.101	3.035	0.88
	QP_4c	0.031	3.073	0.89
Min		**-0.155**	**2.497**	
Max		**0.340**	**3.684**	

Appendix I – Congeneric models

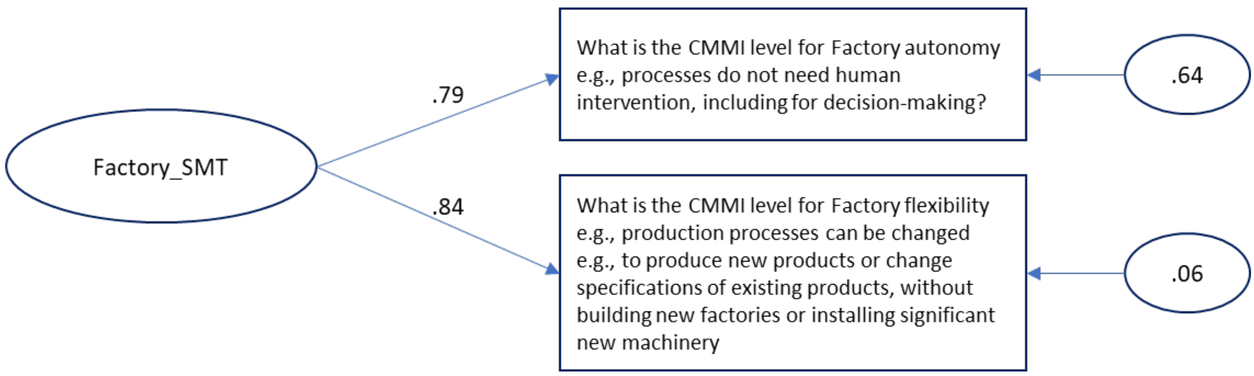
Appendix I.1



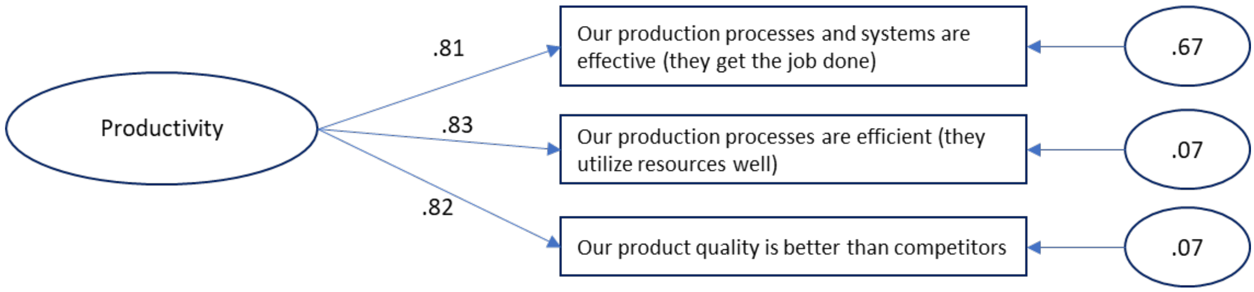
Appendix I.2



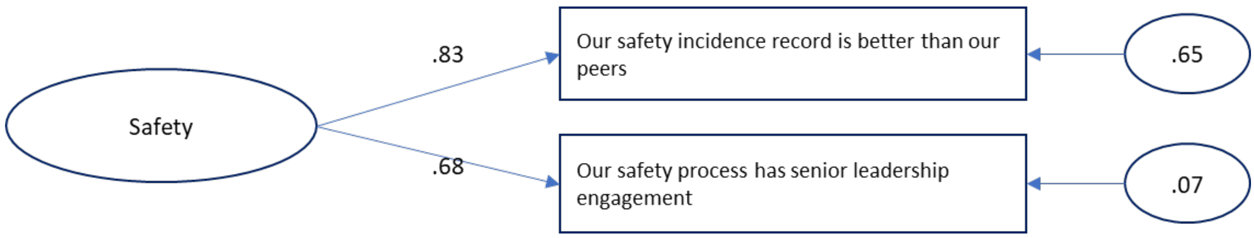
Appendix I.3



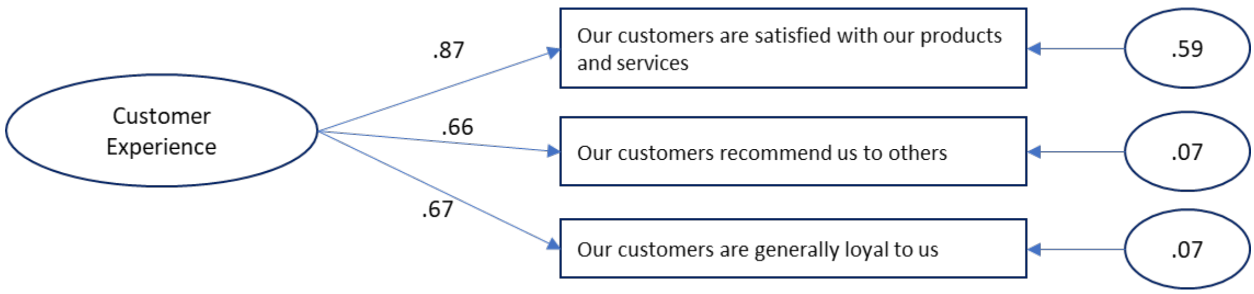
Appendix I.4



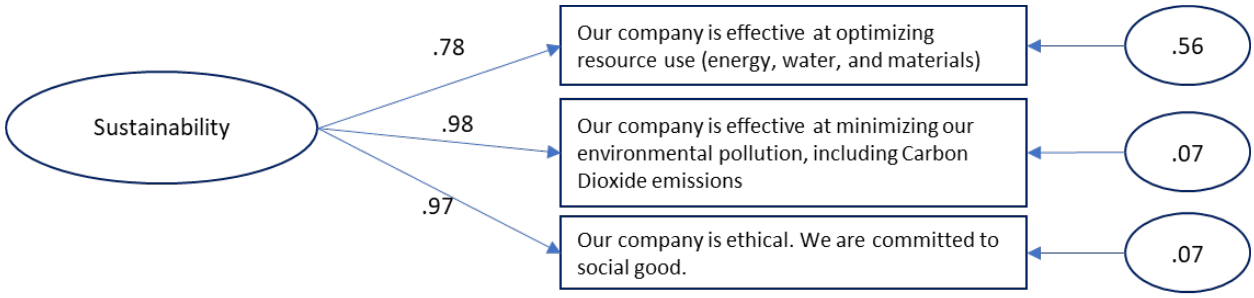
Appendix I.5



Appendix I.6



Appendix I.7



Appendix J – Data Structure

Aggregate Dimension	First-order Concept	Second-Order concepts
Intelligence	Artificial intelligence	Artificial intelligence
	Machine Learning	Machine Learning
Customer engagement	Persistent customer engagement	Customer engagement
Data Capability	Data acquisition	Data Capability
	Data analytics	Data Capability
	Data Capability	Data Capability
	Data processing	Data Capability
	Real-time business intelligence	Data Capability
Data and Information Management	Cloud computing	Cloud computing
	Computing infrastructure	Computing infrastructure
	Edge computing	Edge computing
	Enterprise Information Systems	Supply chain optimization / Interoperability
	Nextgen Communication	Nextgen Communication
Simulation, Visualization, and Remote Interaction	Extended reality	Extended reality
	Live virtual construct	Live virtual construct
Information transparency	Information and data transparency	Information transparency

	Physical virtual information loop	Information transparency
	Visibility	Resource and Process Optimization
Stimuli Responsiveness	Cobots	Cobots
	IoT	IoT
	Robotics	Robotics
	Sensors	Sensors
	Stimuli responsiveness	Resource and Process Optimization
Smartness	Autonomy	Resource and Process Optimization
	Cloud factory	Smart factory
	Flexibility	Resource and Process Optimization
	Flexible production systems	Resource and Process Optimization
	Intelligent actions	Resource and Process Optimization
	Smart capability technologies	Resource and Process Optimization
	Smart enterprise	Resource and Process Optimization
	Smart factory	Smart factory
	Smart operations	Resource and Process Optimization
	Smart processes	Resource and Process Optimization
	Smart product	Smart product
	Smart production and supply chain processes	Resource and Process Optimization
	Smart production systems	Resource and Process Optimization
	Smart solutions	Resource and Process Optimization
	Smart supply chain	Smart supply chain
	Smartness	Resource and Process Optimization
Value	Autonomy	Resource and Process Optimization
	Cloud factory	Economic transformation
		Social value creation
	Connectivity	Resource and Process Optimization
	Cost effectiveness	Economic transformation
	Enhanced Manufacturing capabilities	Resource and Process Optimization

	Enhanced Operating and production processes	Resource and Process Optimization
		Task transformation
	Improved production capabilities	Resource and Process Optimization
	Integrated systems and processes	Resource and Process Optimization
	Intelligent actions	Resource and Process Optimization
	Man-machine collaboration	Task transformation
	Manufacturing cost optimization	Economic transformation
	Mass Product Customization	Mass Product Customization
		Product lifecycle transformation
	New customer experience capabilities	Product lifecycle transformation
	Optimal socio-economic value	Economic transformation
		Social value creation
	Process digitization	Resource and Process Optimization
	Process Efficiency	Resource and Process Optimization
	Process Flexibility	Resource and Process Optimization
	Product development capability	Product lifecycle transformation
	Product lifecycle integration	Resource and Process Optimization
	Production capability transformation	Resource and Process Optimization
	Rapid delivery of customer requirements	Product lifecycle transformation
	Boundary removal	Resource and Process Optimization
	Smart capability technologies	Technology features
	Smart product	Product lifecycle transformation
	Smart solutions	Technology features
	Sovereign Manufacturing Capability	Economic transformation
	Stimuli responsiveness	Technology features
	Superior value realization	Economic transformation
	Value of data	Economic transformation

Digitization	Digital fabrication	Resource and Process Optimization
	Digitization	Resource and Process Optimization
	Digitization of Shopfloor processes	Resource and Process Optimization
	OT (Operating technologies) Digitization	Resource and Process Optimization
Integration	Connected enterprise	Supply chain optimization / Interoperability
	Digital enterprise	Supply chain optimization / Interoperability
	Holistic Enterprise transformation	Supply chain optimization / Interoperability
	Hyperconnectivity	Resource and Process Optimization
	Integrated production enterprise	Supply chain optimization / Interoperability
	Integrated value chain	Supply chain optimization / Interoperability
	OT-IT Integration	Resource and Process Optimization
	Physical virtual integration	Supply chain optimization / Interoperability
	Production capability transformation	Task transformation
Ecosystems	Emergence (System of Systems)	Supply chain optimization / Interoperability
	Integrated systems and processes	Resource and Process Optimization
	Production ecosystems	Supply chain optimization / Interoperability
	Vertical integration	Supply chain optimization / Interoperability

Appendix K – Correlations (Quantitative research)

	Q5_1	Q5_4	Q5_5	Q5_7	Q5_8	Q7_3	Q7_6	Q7_1	Q7_4	Q6_1	Q6_2	Q6_14	Q6_4	Q6_5	Q6_6	Q6_7	Q6_8	Q6_9	Q6_10	Q6_11
Q5_1	1	.501**	.506**	.513**	.516**	.158**	.154**	.406**	.367**	.332**	.366**	.375**	.381**	.291**	.327**	.237**	.266**	.320**	.377**	.378**
Q5_4	.501**	1	.509**	.525**	.461**	.147**	0.093	.288**	.264**	.207**	.161**	.195**	.250**	.205**	.284**	.271**	.217**	.279**	.368**	.360**
Q5_5	.506**	.509**	1	.546**	.498**	.170**	.135*	.318**	.303**	.240**	.245**	.267**	.285**	.221**	.277**	.160**	.180**	.309**	.311**	.321**
Q5_7	.513**	.525**	.546**	1	.490**	.202**	.188**	.377**	.376**	.304**	.302**	.335**	.340**	.294**	.327**	.304**	.246**	.361**	.409**	.392**
Q5_8	.516**	.461**	.498**	.490**	1	.210**	.127*	.318**	.340**	.252**	.272**	.251**	.249**	.261**	.308**	.269**	.190**	.326**	.380**	.372**
Q7_3	.158**	.147**	.170**	.202**	.210**	1	.535**	.342**	.361**	.440**	.459**	.431**	.372**	.322**	.318**	.232**	.261**	.414**	.449**	.428**
Q7_6	.154**	0.093	.135*	.188**	.127*	.535**	1	.335**	.307**	.341**	.371**	.330**	.383**	.301**	.310**	.204**	.255**	.410**	.419**	.407**
Q7_1	.406**	.288**	.318**	.377**	.318**	.342**	.335**	1	.664**	.517**	.517**	.545**	.588**	.475**	.551**	.343**	.378**	.542**	.667**	.649**
Q7_4	.367**	.264**	.303**	.376**	.340**	.361**	.307**	.664**	1	.566**	.560**	.556**	.685**	.512**	.547**	.370**	.387**	.613**	.695**	.680**
Q6_1	.332**	.207**	.240**	.304**	.252**	.440**	.341**	.517**	.566**	1	.672**	.655**	.542**	.488**	.442**	.287**	.280**	.522**	.590**	.585**
Q6_2	.366**	.161**	.245**	.302**	.272**	.459**	.371**	.517**	.560**	.672**	1	.675**	.579**	.486**	.422**	.294**	.253**	.515**	.577**	.570**
Q6_14	.375**	.195**	.267**	.335**	.251**	.431**	.330**	.545**	.556**	.655**	.675**	1	.585**	.509**	.463**	.302**	.291**	.529**	.592**	.588**
Q6_4	.381**	.250**	.285**	.340**	.249**	.372**	.383**	.588**	.685**	.542**	.579**	.585**	1	.564**	.487**	.301**	.308**	.587**	.654**	.649**
Q6_5	.291**	.205**	.221**	.294**	.261**	.322**	.301**	.475**	.512**	.488**	.486**	.509**	.564**	1	.462**	.339**	.334**	.429**	.533**	.525**
Q6_6	.327**	.284**	.277**	.327**	.308**	.318**	.310**	.551**	.547**	.442**	.422**	.463**	.487**	.462**	1	.562**	.575**	.445**	.548**	.562**
Q6_7	.237**	.271**	.160**	.304**	.269**	.232**	.204**	.343**	.370**	.287**	.294**	.302**	.301**	.339**	.562**	1	.516**	.365**	.404**	.407**
Q6_8	.266**	.217**	.180**	.246**	.190**	.261**	.255**	.378**	.387**	.280**	.253**	.291**	.308**	.334**	.575**	.516**	1	.321**	.347**	.359**
Q6_9	.320**	.279**	.309**	.361**	.326**	.414**	.410**	.542**	.613**	.522**	.515**	.529**	.587**	.429**	.445**	.365**	.321**	1	.764**	.751**
Q6_10	.377**	.368**	.311**	.409**	.380**	.449**	.419**	.667**	.695**	.590**	.577**	.592**	.654**	.533**	.548**	.404**	.347**	.764**	1	.951**
Q6_11	.378**	.360**	.321**	.392**	.372**	.428**	.407**	.649**	.680**	.585**	.570**	.588**	.649**	.525**	.562**	.407**	.359**	.751**	.951**	1