# The breadth of Industry 4.0 technologies: factory level dynamic capabilities as antecedents and competitive advantage as outcome

By

Hamed Nayernia

Newcastle University Business School

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Abstract

Technology usage and diversity in factories is nothing new but reaching a point of exponential growth given the continuous commercialisation of better I4.0 technology. These technologies include a growing array of I4.0 ICT, production, and cyber technologies, often deployed by factories in bundles to ensure competitive advantage. Using the theory of dynamic capability second-order integration capabilities were studied as antecedents to the breadth of these I4.0 technologies, examined as a first-order capability. The study examined design-manufacturing integration, manufacturing-strategy integration, and systems integration as second-order integration capabilities. Also, the study examined the link between the breadth of I4.0 technologies and the level of automation, production cost, emission rate, and schedule attainment of the factory as indicators of competitive advantage.

A systematic literature review on the implementation of I4.0 was conducted followed by a pilot study of five semi-structured interviews with industry experts to shape the conceptual model. A survey of senior managers from 320 UK factories was carried out using web-based distribution and data collection to test the model.

The results indicated second-order integration capability of design manufacturing integration and systems integration to act as antecedents to factory manager's first-order capability of adopting and using the breadth of I4.0 technologies at the factory. Manufacturing-strategy integration was not fount to impact the breadth of I4.0 technologies. This study further found the breadth of I4.0 technologies to have a positively and significantly impact the level of automation, emission rate, and schedule attainment of the factory. The breadth of I4.0 technologies was not found to impact production cost. This study contributed to empirically measuring nine diverse I4.0 technologies used at the factory and added to the dynamic capability literature on the dynamic between second and first order capabilities and the benefits for competitive advantage at the factory unit-of-analysis.

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**Related Publications**

Nayernia, H., Bahemia, H. and Papagiannidis, S., 2019. Implementing Industry 4.0: Exploring the literature in a systematic way using text mining.

Nayernia, H., Bahemia, H. and Papagiannidis, S., 2022. A systematic review of the implementation of industry 4.0 from the organisational perspective. *International Journal of Production Research*, *60*(14), pp.4365-4396.

# Chapter 1. Introduction

## *1.1 Research Background*

The use of technology to improve manufacturing is nothing new. In fact, the first industrial revolution, which commenced in the late 18th century, was characterised by the mechanisation of manual processes using steam engines and water wheels (Crafts, 2011; Mokyr, 2018). The second industrial revolution, spanning the late 19th to early 20th centuries, introduced electricity and assembly lines. It led to mass production and further enhanced manufacturing efficiency (Jevons, 1931). The third industrial revolution, which emerged post-World War II, was marked by the onset of digital technology and automation. Computers, electronics, and the internet revolutionized communication and manufacturing processes, transforming the way industries operated (Rifkin, 2011). The term *"Industry 4.0"* (I4.0) originated in Germany and was officially introduced in 2011 at the Hannover Messe trade fair, a testament to Germany's central role in the development of this transformative concept (Schwab, 2017).

Now, in the ongoing fourth industrial revolution (4IR) we are witnessing continued digitisation and the emergence of Industry 4.0. This represents a profound shift for factory operations as it fuses digital technologies, the internet, and physical systems (Lasi et al, 2014; Schwab, 2017; Lee, J. and Lee, K. 2021). Key technologies of Industry 4.0 include the Internet of Things (IoT), artificial intelligence (AI), big data analytics, digital twin, and cyber-physical systems (Frank, Dalenogare, and Ayala, 2019; Zheng et al, 2021). At its core, Industry 4.0 is about the interconnectedness of devices and systems. It enables the exchange of data for intelligent decision-making and automation, underpinned by concepts like the smart factory. This interconnectedness represents a departure from previous industrial revolutions by emphasising the seamless integration of digital technologies with physical systems and the human element (Kagermann et al, 2014).

In further contrast to past technology use in manufacturing, I4.0 represents over a dozen unique sets of advanced production technology. In turn, each technology is further categorised into subgroups optimised for different types of factories and various production strategies. In this light, new measurement methods have emerged to quantify the level of openness to and usage of I4.0 technology (Frank, Dalenogare, and Ayala, 2019; Zheng et al, 2021; Büchi, Cugno and Castagnoli, 2020; Cugno, Castagnoli and Büchi, 2021; Bettiol et al, 2023). For instance, the source of I4.0 has been measured to find out if these technologies have been purchased or internally procured. Equally it is possible to measure the depth of I4.0 and reveal if a specific I4.0 technology is used in other departments of the same business and if other competitors also use this technology. Alternatively, due to the surging number of diverse I4.0 technology platforms it is possible to measure the breadth or number of technologies a specific unit or even sub-unit, such as a factory, use for operations. For a smart factory this represents the capability of factory manager to orchestrate and manage sets of complementary I4.0 technology (Büchi, Cugno and Castagnoli, 2020; Cugno, Castagnoli and Büchi, 2021; Cugno et al, 2022). Of course, the more complex and customised the product the higher the breadth of I4.0 technology needs to be to produce such increasingly complex products in the smart factory (Devaraj, Hollingworth and Schroeder, 2004; Vickery et al, 2016, Kim, 2022; Turco and Maggioni, 2022).

It is crucial to recognise that digital transformation, including I4.0 projects, can fail as possessing technological capacity does not necessarily imply its operational use (Danneels, 2016). The most notable practical limitations include workforce resistance, lack of digital skills, and inadequate change management (Westerman, Bonnet, and McAfee, 2014; Bughin et al, 2018; Cazeri et al, 2022). Therefore, understanding the capability to broaden the number of I4.0 technology platforms and addressing these challenges is vital for a factory management seeking to harness the full potential of digital transformation while not jeopardising their competitive edge in rapidly evolving markets. This is why companies such as Siemens have been able to achieve significant energy savings in production to lower the cost of manufacturing while simultaneously making it more sustainable (Siemens AG, 2022). In other cases, companies such as Nike failed to implement I4.0 at their supply chain as inefficiencies multiplied and other companies such as Tesco only partially realised success as the positive effects of growing efficiency were in part counteracted by fluctuating customer satisfaction (Folarin and Hassan, 2015; Medhi, 2016. p.83).

This shows the significance of clearly understanding the risks and tensions that arise during the digital transformation trek to fully realise and protect I4.0 value. A lack of understanding, misconceptions about the readiness factors, hidden tensions, and unrealistic or unclear performance goals can lead to 85% of I4.0 and digital transformation efforts ultimately failing (Bucy et al, 2016; Facchini, Digiesi and Pinto, 2022). The importance of I4.0 lies in its potential to enhance operational efficiency, innovativeness, and competitiveness (Felsberger et al, 2022; Khan, Ahmad and Majava, 2023). In effect, what sets successful I4.0 initiatives apart is not merely the adoption and use of I4.0 technology but the orchestration and adoption of a set or group of complementary I4.0 technologies for competitive advantage (Cugno, Castagnoli and Büchi, 2021; Bettiol et al, 2023). Such competitive advantage is best realised by ensuring that I4.0 results in customer satisfaction, innovation, and performance gains, such as lowering factory environmental emission rates and improving factory scheduling.

### *1.1.2 Academic Research on I4.0*

Industry 4.0 (I4.0) represents a significant paradigm shift in the world of manufacturing. Accordingly, academic studies surged over the past decade on I4.0. The growing literature on I4.0 overlaps with other similar bodies of literature, some progressing in parallel. In addition to the aforementioned I4.0 technologies, the concept of Industry 4.0 encompasses the study of resources, capabilities, routines, and outcome at various levels. At the holistic level, drivers and barriers in industry and firms have been explored (Saniuk, S. Saniuk, A. 2018; Ghobakhloo and Ching, 2019). On a finer level of analysis, the I4.0 literature explores the various technologies and the multitude of capabilities and resources needed as well as the outcome effects on factories, such as operational and sustainability performance (Črešnar et al, 2020). Still at a more granular level, other studies have explored the data requirements, human resources, and supply chain digitisation implications and benefits of using I4.0 technology (Calabrese, Levialdi Ghiron and Tiburzi, 2021).

The concept of I4.0 is advancing in parallel with similar neighbouring literature on advanced manufacturing technology (AMT), computer-integrated manufacturing (CIM), e-business, digitisation, digitalisation, smart factories, and digital transformation, but it also distinguishes itself from these concepts in important ways, as elaborated below.

AMT encompasses a wide range of technologies, from CNC machining to robotics. While I4.0 leverages some of these technologies, it goes beyond them by integrating them with the Internet of Things (IoT), big data analytics, and cyber-physical systems (CPS). I4.0 is about creating intelligent, interconnected systems that can optimise processes and make real-time decisions. Studies indicate that I4.0 extends the capabilities of traditional AMT by connecting machines and processes in a way that enables data-driven decision-making (McDermott and Stock, 1999; Chung and Swink, 2009).

CIM has been instrumental in automating manufacturing processes, but I4.0 builds on CIM's foundation by incorporating real-time data exchange, AI, and the Industrial Internet of Things (IIoT). It enables adaptive and reconfigurable manufacturing, where production processes are adjusted based on real-time data, leading to increased flexibility and efficiency. Studies indicate that I4.0 is an evolution of CIM, integrating the physical and digital worlds to create smart factories (Ivanov et al, 2021; Pereira, Szejka and Canciglieri 2022).

Smart factories and smart manufacturing are an integral part of I4.0, but they are not synonymous. A smart factory leverages technology to improve manufacturing processes and efficiency. I4.0 goes further by integrating smart factories into a broader network, connecting them with suppliers, customers, and other stakeholders for end-to-end integration and optimisation. Studies distinguish between smart factories and I4.0, emphasising the role of I4.0 in creating a network of intelligent, connected smart factories (Saniuk, S. Saniuk, A. 2018; Wang et al, 2021).

While I4.0 leverages automation and data analytics to optimize processes, Human-Centric Manufacturing emphasises collaboration between human workers and machines, with technology enhancing human skills (Björklund et al, 2019). This idea of human-led-digitisation is expanded by the I4.0 literature (Sivathanu and Pillai, 2018; Da Silva et al, 2022; Nankervis and Cameron, 2023). In this vein, I4.0 focuses on automation and technology while considering the symbiotic relationship between humans and technology. Integrating aspects of both approaches may be beneficial for companies seeking to balance efficiency with human empowerment and creativity in the modern manufacturing landscape.

E-business primarily focuses on digital interactions between businesses and customers. In contrast, I4.0 expands the scope beyond just e-commerce. It integrates e-business principles into the manufacturing process itself by enabling seamless communication between machines, products, and systems, leading to more efficient production and supply chain operations. Recent research highlights the integration of e-business into I4.0, emphasising its role in creating new business models and enhancing customer experiences (Sanders, 2007; Benitez et al, 2018).

While both digitisation and I4.0 involve the conversion of analogue information into digital formats, digitization is a fundamental step toward I4.0 implementation. I4.0 takes digitisation a step further by using digital data to drive automation, decision-making, and connectivity across the entire manufacturing ecosystem. Recent literature highlights the pivotal role of digitisation as the foundation of I4.0, emphasizing the importance of data in achieving smart manufacturing (Lorenz et al, 2020; Björkdahl 2020).

Digitalisation is an extension of digitisation beyond business. It uses analogue to digital conversion of broader infrastructure to transform business operations which may not necessarily be manufacturing related. I4.0 represents a higher level of digitalisation, where data-driven insights and automation are embedded into every aspect of the manufacturing ecosystem. It moves from merely using digital tools within silos to become a digital enterprise. Research on this topic explains the transition from digitalisation to I4.0, highlighting how companies are moving beyond technology adoption to drive a digital production economy (Chen, Despeisse and Johansson, 2020).

Digital transformation refers to the comprehensive change in business processes and models through the integration of digital technologies. I4.0 is a subset of digital transformation, specifically targeting the smart factory. It embodies the digitisation and digitalisation principles within the manufacturing domain. Recent studies illustrate how I4.0 is driving digital transformation in manufacturing, leading to enhanced competitiveness and sustainability (Kagermann et al, 2020; Ceipek et al, 2021; Mao, Liu and Gong, 2023).

### *1.1.3 Limitations of I4.0 Research*

A review of the I4.0 implementation literature reveals several theoretical and practical limitations hindering research and adoption. For instance, terminology and definitions are sometimes used confusingly if other concepts (e.g., digitalisation) are combined with I4.0 in research (Liao et al, 2017; Smith et al, 2021). Recent research has highlighted the struggle for scholars to keep up with the continuous evolution of technology and expanding terminology such as I5.0 (Renda et al, 2021; Calabrese, Levialdi Ghiron and Tiburzi, 2021; Miller, 2022; Maddikunta et al, 2022; Ivanov, 2023). Also, the rapid pace of technological advancements in I4.0 remains a pressing issue, especially for smaller, less resourceful factories (Horváth and Szabó, 2019; Stentoft et al, 2021).

Despite the field's growth in defining the requirements at the industry, firm, and to a lesser degree, sub-unit levels, the human element, data aspects, and supply chain implications suffer from shortage of empirical research to verify I4.0 claims (Raj et al, 2020). Recent studies underscore the need for more management-centric empirical investigations at the sub-unit levels to bridge the gap between theory and practice by using theory to explore hidden tensions and complexities at the sub-unit level (Nayernia, Bahemia and Papagiannidis, 2022; Gupta et al, 2023). The above is in addition to inherent limitations, such as the persisting issue of limited cross-disciplinary collaboration in I4.0, despite its inherently cross-disciplinary nature (Chen, 2020; Ivanov et al, 2021).

I4.0 studies focusing on evidence-based empirical findings still rely on single-case studies, small sample sizes and a general firm level unit-of-analysis. In most cases, a theoretical foundation for the study is completely missing or hardly ever referred to in interpreting I4.0 effects (Nayernia, Bahemia and Papagiannidis, 2022). This can lead to overlooking the hidden requirements for, or missed opportunities of, I4.0 at the factory. Also, this can result in misrepresentation of the antecedents and outcomes for hands-on sub-units, where I4.0 is typically used. For instance, the capabilities, routines, and priorities of firm-level managers may not match with those of sub-unit- decision makers, such as factory and operation managers. Therefore, generalisation about the causal relations of I4.0 initiatives at the firm level do not translate to the same results at the sub-unit level, such as the factory (Miller, 1978; Gattiker and Goodhue, 2005). Also, in practice critical decisions such as resource allocation often rest with top firm-level stakeholders instead of sub-unit managers such as operations managers, factory managers, and supply chain managers, who are most knowledgeable about operational issues. This is the case even if I4.0 technology is being implemented at the factory. Therefore, a lack of empirical studies on I4.0 at the factory-level has led to many misrepresentations and confusion about I4.0 requirements and outcomes. In this vein, studies calls for a broader set of case studies to address this limitation.

More recent studies directly emphasise this weak point in the literature and call for increasing investigation of the paradoxes, contradictions, and tensions inherent in managing the current breadth of I4.0 and even for growing the breadth of I4.0, in time exposing the dark sides and hidden pitfalls (Raj et al, 2020; Dieste, Sauer and Orzes, 2022; Moschko, Blazevic and Piller, 2023; Dieste et al, 2023). Thus far, I4.0 studies at the factory level exploring the above tensions and the needed trade-offs that factory managers need to consider are very rarely found in the literature. Examples include the study of synergies and trade-offs between I4.0 and lean manufacturing at the factory (Sartal, Llach and León-Mateos, 2022).

Other classic management mechanisms such as integration, whether internal or external, are not well studied and completely ignore the factory level. Although integration is emphasised by empirical firm-level studies, the outcome rarely represents the struggles and difficulties of operational integration complexities present on the factory floor. This has resulted in not well understood and even less studied mechanisms and capabilities for integrating factory operations with other important business aspects (Swink and Nair, 2007), for instance, with the strategy of the business, other functions such as R&D, design, marketing, and sales (Swink and Song, 2007). The lack of a coherent stance towards the digital transformation at the factory results in impulsive and uncoordinated responses to challenges, which other connected departments at the factory perhaps would not fully comprehend.

Equally as limiting is the lack of understanding of deliverable I4.0 outcomes at the level of the factory. Thus far, the literature has explored the innovation and other advantages firms benefit from. Also, the literature has focused on organisational performance (Duman and Akdemir, 2021), product innovation performance (Sarbu, 2022; Fragapane et al, 2023) and supply chain performance (Reyes, Mula and Díaz-Madroñero, 2023) but not operational performance at the factory. Unsurprisingly, the outcome of adopting technology such as CNC at the factory improves the level of process automation (Ritzman and Safizadeh, 1999). However, the use of multiple I4.0 technologies is not related empirically to the level of automation at the factory. It is also relatively unknown what the adoption of groups of I4.0 technology means for production costs and schedule stability. In the same vein, the effect of using multiple I4.0 platforms is not known in relation to the effect on schedule stability and schedule attainment of the factory, nor does the literature elaborate on the factory sustainability measures such as emissions rates and green technology at the factory (Klassen and Waybark, 1999; Zhu and Sarkis, 2004).

From the practical perspective, implementing I4.0 in competitive markets with often limited resources is not straight forward. In the UK, the 2023 manufacturing sector accounted for 9.3% of the gross value added and 8.1% of the employment force (ONS, 2024). However, after the recent Covid-19 pandemic the manufacturing sector has been stagnant, and in some cases declining. It is evident that such difficult market conditions hinder the adoption of expensive production technology. Moreover, being able to adopt I4.0 is not factory specific and other factories can also use the same combination of technology and in some cases implement them in a more cost effective and successful manner. This is also because factory managers focus more on ordinary capabilities that primarily consider maintaining current capability to stay in the market as opposed to higher-order capabilities and practices related to transformative, routine changing routines, which could broaden the value of I4.0 technology. In this context, the combination of first and second order capability of the factory can create difficult to imitate value and sustain competitiveness. However, such combinations of capabilities often lack prioritisation with factory managers often prioritising more pressing issues related to the daily operation of the factory.

In general, still vaguely understood theoretical and practical causes and consequences of I4.0 and the fact that an increasing number of technology platforms need to be orchestrated for I4.0, compared to AMT and CIM, complicates matters quickly if the capability to support the breadth of I4.0 technology is missing. It soon becomes evident that implementation could be highly complex, risky, and prone to failure if factory managers avoid an integrated approach. Questions therefore emerge regarding the importance of factory integration capability to improve the effectiveness of managing the breadth of I4.0 technology. Other pressing questions remain regarding the actual factory performance given the different breadth of I4.0 for various factory sizes and for factories with different production strategies.

### *1.2 Research Objectives*

The research uses dynamic capability (DC) theory, and the objective is twofold: to clarify the relevance of integration capability as an antecedent to using sets of I4.0 technology in factory production; and to find the effect on factory performance. It is apparent that implementation is contingent on a multitude of factors, such as factory size, age, and production strategy as well as other difficult to measure factors contributing to the rate success of I4.0 implementation. To explore the strategic significance of I4.0 this study measures capabilities, routines, and resources and tests the interaction among them for bolstering the competitive advantage. Two main research questions are addressed in this research:

1. Can transformational integration capability of factory managers benefit the capability to implement the breadth of I4.0 technologies at the factory?

2. Does the capability to implement the breadth of I4.0 technologies at the factory lead to improved performance and competitive advantage of the factory?

Based on the DC theory, the first objective is to find the relevance of higher-order integration (dynamic) capability on the (ordinary) capability to implement the breath of I4.0 technologies. The aim is to better understand how such higher order integration capabilities impact the important yet imitable capability to implement the breadth of I4.0 technologies. The second objective is to determine the impact of the breadth of I4.0 technologies on factory operational performance, such as the level of automation, production cost, environmental sustainability, and schedule attainment. For this, the aim is to find how first order capability, supported by second order capability provides competitive advantage gains.

In addressing the first research question, we explore how tangible and intangible resources are fundamental in the pursuit of I4.0 excellence. Recent literature emphasises the pivotal role of scalable resource bundles in the digital transformation journey (Giustiziero et al, 2023). Routines, encompassing established procedures and practices, play an integral role in facilitating the seamless adoption and integration of I4.0 technologies (Danneels, 2016). Recent studies have highlighted the point that well-structured routines are essential in ensuring that these technologies are effectively adopted and leveraged, resulting in improved factory performance and breadth of I4.0 (Ghosh et al, 2022; Felsberger et al, 2022; Csiki, Demeter and Losonci, 2023). Studies highlight the need to view capabilities, routines, and resources as enablers of not just technological adaptation, but also as vehicles for cultivating an agile, forward-looking culture that can swiftly learn, and adapt to the ever-evolving I4.0 landscape as competition also starts to use the same I4.0 technologies (Gupta et al, 2023).

Capabilities, particularly higher-order capabilities, such as integration capabilities, have emerged as indispensable tools for knowledge transfer. These capabilities empower factory managers to not only broaden the number or breadth of I4.0 technologies used in the factory but also to reconfigure and optimise their current production assets (Giustiziero et al, 2023). Integration capabilities are recognised as critical drivers, enabling smart factories to efficiently harness an array of I4.0 technologies (Benitez, Ayala and Frank, 2020; Morgan et al, 2021; Tortorella et al, 2021; Ghobakhloo et al, 2023).

Internal integration, which involves aligning various functions within a factory, is essential for enhancing the comprehensive implementation of I4.0 technologies (Tabim, Ayala, and Frank, 2021). The integration of employees and data into the digital domain is another crucial aspect, as it fosters dynamic capabilities, organisational learning, and cross-functional cooperation, all of which are vital for realising the benefits of I4.0 transformation (Karimi and Walter, 2015;

Hanelt et al, 2021; Galanti et al, 2023). In this context, the cross-functional integration of production with design and strategy functions is expected to improve the factory managers' ability to manage a range of I4.0 technology platforms in tandem. On the other hand, external integration, particularly along the supply chain, allows for greater collaboration and connectivity with partners, enabling a more holistic systems integration and efficient I4.0 implementation (Peng et al, 2013; Jayaram and Xu, 2013; Cheng, Farooq and Jajja, 2021).

These two forms of integration, when well-executed, work in tandem to orchestrate a higher number or breadth of I4.0 technologies, providing factories with a competitive advantage and a pathway to improve the level of automation. The finer objectives of this study also explore the effect of factory management capability to implement the breadth of I4.0 technologies on the cost of production, constituting a major decision factor for any technology investment. Similarly, the study aims to investigate the effect of factory management capability to implement the breadth of I4.0 technologies on the environmental sustainability of the factory and the rate of emissions specifically.

In addressing the second research question, we explore how the usage of multiple I4.0 technologies in tandem impacts factory performance. This brings up critical objectives to explore, such as the factory's level of automation, production costs, emission rates, and schedule attainment in cases of a high breadth of I4.0 in particular types of factories or sectors. The aim for the second objective is to reveal the importance of factory managers' capability to deploy and use broad I4.0 technology platforms, enabled by integration capabilities, to gain competitive advantage. As previously noted, factory managers' capability to deploy and use broad I4.0 technology platforms can be imitated over time by the competition and has to be coupled with higher-order capability, such as design-manufacturing integration, manufacturing-strategy integration, and systems integration capabilities, to protect I4.0 value.

### *1.3 Methodology Overview*

This research employs a mixed-method approach that combines deductive and inductive methods. Initially, the deductive approach is used to navigate the evolving I4.0 literature, followed by the inductive approach for theory testing (Forza, 2002). The primary focus is on the UK's manufacturing factory managers involved in I4.0 technology adoption. The initial systematic literature review (SLR) explores the *"industry 4.0 implementation"* literature, using full-text mining to cluster the main topics of discussion based on frequency and case occurrence. This provides an unbiased categorisation of the main themes emergent in the literature. The SLR ultimately reviews eleven streams of research across five levels. Quantitative exploration of each research stream further identifies the gaps and limitations of the literature. The second phase of the research employs a cross-sectional survey of 320 UK factories. The unit of analysis is at the factory level and senior managers such as factory managers, directors, supervisors, and operations managers, serve as the key informants and primary respondents due to their comprehensive industry knowledge and knowledge about their own factory compared to the competition (Gattiker and Goodhue, 2005; Rosenzweig and Easton, 2010).

Data collection involves two stages: a pilot study using semi-structured interviews to refine the variables and a main survey using a web-based questionnaire in a clear and concise format (Forza, 2002; Reja et al, 2003). The research uses random sampling to ensure representation of the population. Eligibility criteria and filters within the online data collection platform help select appropriate participants (Forza, 2002; Lefever, Dal and Matthíasdóttir, 2007). This research employed web-based surveys as the data collection method, as this offered several advantages, including lower costs, higher response rates, and the ability to reach a large sample of participants. The use of Prolific as a distribution platform facilitated the efficient management of responses, ensuring valid and complete data collection (Dillman, Smyth and Christian, 2009). This research method is rigorous and well-suited to providing insights into the relationship between factory capabilities, the breadth of I4.0, and factory performance.

In the confirmatory data analysis stage, multiple tests are conducted, encompassing reliability and validity checks, multiple regression, and structural equation modelling (SEM). Construct validity is assessed using confirmatory factor analysis (CFA) in AMOS (Hair et al, 2019). Modification indices are considered when justified theoretically, and convergent validity is evaluated using average variance extracted (AVE) (Hair et al, 2019). Multiple regression analysis is applied to determine the impact of multiple independent variables on a dependent variable. Assumptions related to multicollinearity, linearity, normality, outliers, and homoscedasticity are examined to minimize type 1 and type 2 errors (Ganzach, 1998; Tabachnick and Fidell, 2007; Garson, 2012; Hair et al, 2019). For hypothesis testing, AMOS SEM is employed, combining regression and factor analysis to address complex relationships (Hoyle, 2012).

### *1.4 Findings*

The results of this study shed light on two previously understudied streams of research related to the antecedents and outcome of using broad I4.0 technologies. At a finer level, this study contributes to the I4.0 literature. This study measures factory manager capabilities and factory performance outcomes not previously linked to the breadth of I4.0. The findings deal with an important limitation in the literature by showing the importance of combining different types of capabilities at the factory to not only gain I4.0 value but to also protect it and ensure competitive advantage.

The results show the relationship between higher-order capabilities related to learning and transformation and the strengthening effect on more easily imitable lower-order capability. In this case three higher-order integration related capabilities are found to improve the capability of factory managers to deploy broader types of I4.0 technology to enhance factory competitiveness (Büchi, Cugno and Castagnoli, 2020; Teece, 2023). The results concur with and add to similar dynamic capability research highlighting the transformative potential of I4.0 in manufacturing (Li et al, 2022a; Felsberger et al, 2022; Lu, Zhao and Liu, 2022; Sulistyo and Ayuni, 2023; Rehman and Jajja, 2023; Yavuz et al, 2023; Arcidiacono et al, 2023).

On the first research question, this study identified design-manufacturing integration, manufacturing-strategy integration, and systems integration as second-order or higher-order dynamic capabilities. These capabilities enable top factory managers to create new learning routines and transform existing resource bundles (Danneels, 2016; Teece, 2023). Specifically, the results indicate that factory managers who are strong in design-manufacturing capability are more capable of managing the breadth of I4.0 technologies. In this context, strong design-manufacturing capability empowers factory managers with the knowledge to integrate I4.0 design technology with I4.0 ICT and production technology (Swink and Nair, 2007).

The results further indicate that factory managers who are strong in systems integration capability excel at the capability to manage the breadth of I4.0 technologies. In this sense, the results of the SEM testing show that factory managers who are strong in systems integration capability better understand the need to integrate the multitude of internal and external systems to ensure the flow of data and reflect downstream customer demands in real-time (Schroeder and Flynn 2001). Interestingly, the results of the SEM testing reveal there is insufficient evidence to indicate manufacturing-strategy integration results in the capability to manage the breadth of I4.0 technologies. The results speak to the ongoing debate on whether business strategy drives manufacturing strategy or vice versa (Pozzi, Rossi and Secchi, 2023). In this case, it is apparent that factory managers who are well versed in the capability to integrate manufacturing operations with business strategy are not necessarily more capable of managing the breadth of I4.0 technologies at the factory.

On the second research question, the study shows the competitive advantage gains of a dynamic capability approach to I4.0 at the factory level. The results indicate increasing factory performance across multiple indicators as a result of first-order capability of factory management capability to implement the breadth of I4.0 factory technologies. First, we show that the breadth of I4.0 technology is positively linked to the level of automation and specifically processes automation at several stages on the factory floor. Empirical measurement of the level of process automation at the factory level fills an important and pressing gap as automation is often regarded as a given outcome and not often measured in cases where a set of orchestrated I4.0 technology is deployed. Second, the results indicate that the capability to implement the breadth of I4.0 technology lowers the rate of toxic factory emissions and improves the environmental sustainability of the factory. This provides critical evidence to support the case for using broad and diverse sets of I4.0 technology, some specifically used for energy saving (Hasan and Trianni, 2023). Such environmental sustainability gains as a result of a more resourceful combination of factory technology has long been considered to drive competitive advantage (Shrivastava, 1995; Lohmer, Kossmann and Lasch, 2022). Third, a similar positive and significant relation, although to a lesser extent, is found between first order-capability to implement the breadth of I4.0 technology and schedule attainment of the factory. These findings show that factories are better able to keep up with customer orders if the capability to implement the breadth of I4.0 is more strongly developed and exercised by factory management.

Based on the dynamic capability theory this study contributes to the ongoing discussion on the link between capabilities, resources, and competitive advantage in factories. Addressing the second questions contributes to the debate on trade-offs between various factory performance goals by showing that automation and the control of emissions improve more rapidly, while the impact on production costs may take longer to materialise and, in some cases, show growing production costs as a result of inefficient deployment or a lack of integration of some technologies within the breadth of I4.0 technologies used in the factory.

This observation resonates with prior studies regarding similar production technology use (Schweikl and Obermaier, 2020). Additionally, we highlight the point that broader use of I4.0 technology, while beneficial, does not represent the whole picture of technology adoption success (Iansiti and Lakhani, 2020).

### *1.5 Thesis Structure*

This thesis is structured into seven chapters. Chapter two delves into the existing literature related to the origin of I4.0, the breadth of the adopted I4.0 technology, and the resource-based dynamic capability view, which serves as the foundational theory for this study. This systematic literature review identifies gaps in the I4.0 implementation literature and establishes the research questions and objectives for the study based on the limitations. Chapter three outlines the core theory and the mechanisms of DC. This chapter build the hypotheses examined in the thesis and expands on their development. Chapter four focuses on the methodology, including the research strategy and the creation of the research instruments. Chapter five presents the data analysis and highlights the key findings of the study. Chapter six discusses the overall research outcomes in the context of existing studies, discussing the findings of the wider literature and the survey results. Finally, in chapter seven, concluding remarks are offered, along with a summary of the theoretical contributions, managerial implications, limitations of the study, and suggestions for future research avenues.

# Chapter 2. Literature Review

## *2.1 Chapter Introduction*

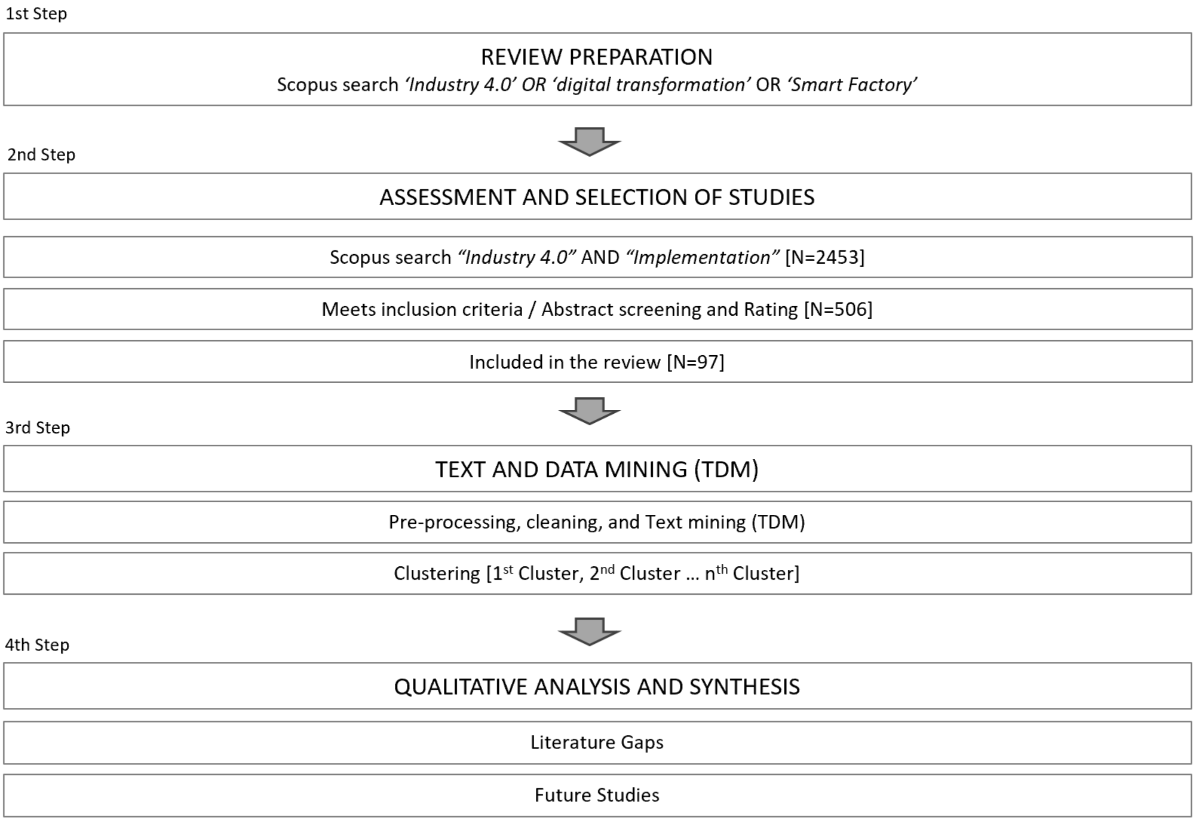
The following chapter sheds light on the state of the I4.0 implementation literature. Initially the chapter offers a map and analysis of the literature and how the systematic literature review process was conducted in four steps. To better understand literature trends, the limitations of past reviews were clarified. 97 research articles were subject to careful qualitative analysis, selected based on the systematic literature review process. The chapter includes results for keyword and thematic clustering based on full-text mining of each included case (article). Eleven research streams were identified across five levels relevant to I4.0 implementation, namely, industry and firm, smart factory, data, human resources, and the supply chain level. The chapter concludes with the gaps in the I4.0 implementation literature, and proposed avenues for future research.

## *2.2 Literature Mapping and Analysis*

The literature review on I4.0 is conducted in five steps, as shown in figure 1. The first stage examines prior review studies trying to define I4.0 within a multitude of academic disciplines, researching specifically the implementation in manufacturing. This initial step enriched the planning and preparation stage for systematically selecting studies for the review stage. Beyond clarifying the working definition, this stage examines the topic of I4.0 implementation from a holistic perspective. The second stage systematically screened, rated, and selected the studies for the review step.

This is to avoid studies extending beyond the core literature on the implementation of Industry 4.0 from the organisational perspective. This stage is guided by best practice for reviewing such a rich and diverse body of literature (Tranfield, Denyer and Smart 2003; Denyer and Tranfield, 2009). In order to overcome subjectivity in categorisation of studies and the main themes discussed, in the third step a full-text mining was conducted on the corpus of the selected studies to cluster the main topics discussed (Davlembayeva, Papagiannidis and Alamanos, 2020).

*Figure 1 Literature Review Process*




This method reduced the subjective, deliberate, and therefore biased grouping of topics studied, instead grouping similar topics into clusters based on frequency and number of cases. Because thus far only the literature on I4.0 and not manufacturing is reviewed, the fourth step screened, rated, and selected studies at the factory or organisation level related manufacturing openness and integration as well as manufacturing performance. The final fifth step qualitatively reviews the 97 selected studies. Accordingly, I4.0 literature findings are discussed from section 2.4.1 to section 2.4.5, while the manufacturing core literature findings are elaborated in sections 2.4.6 and 2.4.7 respectively.

### *2.2.1 Step 1: Review Preparation*

A preliminary examination of the literature was conducted to facilitate the identification and clarification of the research gaps within the literature from multiple angles. This supported the formulation of the research objectives and the aim of the literature review. This stage included the study of extant literature reviews on Industry 4.0 and advanced technology implementation within manufacturing. The reviews were selected in Scopus, searching for journal reviews in English using either the keywords *'Industry 4.0'*, *'digital transformation'* or

*'Smart Factory'* in the title, abstract or keywords. Excluding highly technical papers not related to manufacturing or industry (e.g., medical, biochemistry or physics) returned 1290 review studies as of November 2022, with 303 systematic literature reviews related to manufacturing technology (See Appendix A). An initial review of extant studies on implementing I4.0 and the manufacturing literature identified several limitations related to the lack of a management-centric view on implementing I4.0. Equally critical, empirical studies exemplifying and validating I4.0 implementation cases are largely missing from the literature. This is critical in identifying the causes (enablers) and potential outcome of I4.0, necessitating further research (as examined in section 2.5).

*2.2.2 Step 2: Industry 4.0 Literature study selection and assessment*

To capture the full spectrum of data contained in the pool of papers on I4.0, all the articles with the keywords 'Industry 4.0' and 'Implementation' featured in the title, keywords or abstract of the paper were selected from the Scopus database, as of February 2021. The Scopus database is user-friendly, includes a wide range of journals (approximately 20% more coverage compared to the Wen of Science database) and is more consistent than other databases like Google Scholar (Falagas et al, 2008). Articles available in full-text and in English were included in the initial search criteria. No limits were set on the publication year. Subject areas were filtered to exclude highly technical domains (e.g., mathematics, chemical engineering, medicine) while including subject areas relating to or within the management research domain, which reduced the number of articles to 506. The articles were then subjected to an independent screening by two additional reviewers, who reviewed the meta information (title, abstract, keywords). At this final screening stage all papers were rated from zero to two, based on the relevance to the review's research objectives.

After rating the 506 articles, 52 papers were given an average rating of 2, representing studies with a direct link to implementation. As for the remaining cases, 45 papers were rated between 1.5 and 2, showing a high link to implementation. And lastly, the 375 papers rated below 1.5 were removed since they showed indirect or only a partial relation to implementation. In total, 97 articles rated above 1.5 were included in the systematic literature review. Appendix B provides descriptive statistics of the selected papers. To summarise, the pool of 97 selected articles were mostly published in the period from 2018 to 2021 and originated from diverse academic sources. The studies predominantly represented the management domains (e.g., decision science, social science, finance, and accounting). Therefore, as I4.0 is studied by interdisciplinary researchers, multidisciplinary management studies often overlapped with other neighbouring fields of research. For instance, some management studies expanded into the engineering and computer science subject areas, while others touched on the energy and environmental aspects of I4.0. Most studies (79%) were empirical, including thirty-nine surveys and questionnaires and twenty-two case studies. The remainder of the papers (21%) were conceptual. The selected studies were mostly (60%) conducted at or relevant to the firm-level unit of analysis. In comparison, fewer studies focused on important subunits such the plant or factory level of analysis.

*2.2.3 Step 3: Industry 4.0 literature text and data mining*

This step extracted data from the full text of the selected 97 studies on I4.0 implementation. Due to the fast-evolving and to some degree vague nature of the I4.0 literature, the entire text of the manuscripts was subjected to text mining as opposed to only the abstract (Westergaard et al, 2018). The text and data mining (TDM) operation comprised three successive phases. Initially the studies were pre-processed followed by the actual text mining operation and ultimately the clustering of main themes and keywords discussed by the selected studies.

The pre-processing step aimed to clean the data within the articles to isolate the core paragraphs discussing I4.0 for each case. This cleaning stage included the removal of figures and images as well as the data contained within brackets “()” and braces “{}”as this presented irrelevant or duplicate information. To simplify the data extracted, during the pre-processing stage words highly similar in meaning (e.g., firm and company) were replaced by one term. Also, plural and singular versions of the same terms as well as acronyms were standardised and replaced with single word terms to avoid duplicate results during the analysis. Lastly, redundant, and duplicate textual data not relevant to the core findings of the research was removed, for instance, journal details, article keywords, author details and other segments scattered across the references and appendices.

After the pre-processing stage the cleaned manuscripts representing the corpus were transferred into the text mining software. In this case Wordstat (QDA miner add-on software) for quantitative full text analysis was used. To clarify the most predominant themes and topics discussed within the corpus, the keyword frequency analysis (limited to 100 results) and phrase frequency results were analysed to quantify the most discussed phrases and words used. To support this stage the top keywords were examined in the 'keyword-in-context' function of QDA miner for every term. This exposed the list of manuscript segments from which the term had originally been extracted. This allowed for verification and validation of the exact semantic meaning of the phrases or keywords, particularly when terms were often generalised. In addition, the term frequency-inverse document frequency (TF*IDF) of the top keywords was reviewed to distinguish the terms frequently discussed but only by a few cases. Extraction of the keywords and mapping of the interconnectedness among them revealed the relation of similar terms that had the same meaning or are used within the same context, characterising the content of the corpus (Ananiadou et al, 2009). The quantitative text and data mining revealed the clusters of management issues most predominantly discussed within the I4.0 implementation literature (discussed in section 2.3.2).

#### *2.2.4 Step 4: Qualitative analysis and synthesis*

The qualitative review of individual cases was divided into two sequential steps. Initially the abstracts of the papers were again reviewed to clarify the diverse spectrum of studies and the main topics discussed. This was followed by a systematic and critical review to determine the aim of the study, clarify the methodology, and assess the findings of the paper by carefully reading through the body of the text. Synthesis remains a complex process of the review as it is necessary to describe the set of the research identified, assess the reliability of the research outcomes, combining similar findings into groups (Ananiadou et al, 2009). Multi document summarisation (MDS) aims to extract and condense the most salient information collected during the text mining and review stage (Okazaki Matsuo and Ishizuka, 2005). A summary of the most predominant is presented in section 2.4. For this research, particular attention has been paid to following a coherent article structure, choosing the right balance between breadth and depth, and focusing on concepts (concept-centric) by thematically structuring the review section, as opposed to a chronological or alphabetical structure of the extant publications (Fisch and Block, 2018).

### ***2.3 Past Reviews and Text-mining Results***

#### *2.3.1 Past Reviews*

Initial reviews tried to understand the general requirements and issues of I4.0 (Liao et al, 2017) and the smart factory (Strozzi et al, 2017). They clarified keywords and terminology for the concepts, while not delving into granular and context specific causes and consequences of I4.0. Initial reviews instead examined such transformation as a multi-level paradigm.

Review studies clarified priorities for I4.0 and further emphasised the importance of academic research into the diverse and often hidden enabling preconditions and wide-ranging emerging application fields. Other reviews also clarified the definition (Culot et al, 2020) and the multitude of requirements for I4.0, such as making sense of the various maturity and readiness models (Hajoary, 2020) and increasingly studied sustainability and environmental aspects of I4.0 (Kamble, Gunasekaran, and Gawankar, 2018). Similar reviews have tried to understand universal and general I4.0 issues such as interoperability (Lu, 2017) and the evolution of digital strategies in manufacturing in the past half century (Dohale et al, 2022). The above reviews tend to clarify definitions, involvement, and expectations, instead of objective analysis of specific theoretical and practical needs and implications.

As I4.0 became more understood, reviews focused on specialised applications, revealing trends in specific sectors. For example, specific implementation scenarios such as I4.0 in the construction industry clarify the paradoxes inherent in large-scale technology adoption (Dallasega, Rauch, and Linder, 2018). Other diverse sectors are also reviewed, such as ship building (Ramirez-Pena et al, 2020), the automotive sector (Wankhede and Vinodh, 2022), the wood industry (Molinaro and Orzes, 2022), the food industry (Sharma, Tyagi and Bhardwaj, 2020; Kayikci et al, 2022; Stefanini and Vignali, 2023), the agriculture industry (Vernier et al, 2021), and the textile industry (Nouinou et al, 2023). Such findings are not necessarily applicable to other manufacturing sectors, and reviews comparing similarities and differences between I4.0 sectors are lacking. These reviews limit the understanding of strategy and management needed for a successful I4.0 journey, such as trade-offs during implementation.

As I4.0 strongly depends on the technologies adopted in the organisation, these technologies are reviewed. For instance, recent reviews have explored deep learning in production systems (Panzer, Bender and Gronau, 2021; Serey et al, 2023) and artificial intelligence for manufacturing processes (Toorajipour et al, 2021; Eren, Demir and Mistikoglu, 2023; Singh et al, 2023). Other reviews have focused on blockchains (Queiroz, Telles, and Bonilla, 2020), Digital twins (Semeraro et al, 2021; Atalay et al, 2022; Touckia, 2023; Mu et al, 2023) and other supplementary technology such as cybersecurity (Corallo et al, 2022; Kampourakis, Gkioulos and Katsikas, 2023) and cyber manufacturing (Andronie et al, 2021).

Other technology-centric reviews try to understand the process of I4.0 technology implementation (Stornelli, Ozcan, and Simms 2021), particularly for technologies with a wide range of applications (Zheng et al, 2021). For example, Dolgui, Sgarbossa, and Simonetto (2022) reviewed the process of adopting I4.0 in assembly systems. Similarly, Silvestri et al, (2020) examined maintenance transformation, and Zonta et al, (2020) reviewed the predictive maintenance capabilities of I4.0. Such technology-centric reviews also analysed the impact of specific I4.0 technology on the business, for instance, the impact of IoT on changes in corporate business model (Palmaccio, Dicuonzo, and Belyaeva, 2021) and digital servitisation (Paschou et al, 2020). While the above reviews clarify technological progress, a strategic approach to technology adoption is missing.

In contrast to the past reviews above, other reviews have emphasized the need to study I4.0 from the management perspective (Schneider, 2018; Piccarozzi, Aquilani and Gatti, 2018). Such focused reviews partially examine the organisational and management aspects of I4.0 technology. For instance, Wagire, Rathore and Jain, (2020) reviewed the dynamics of I4.0 and the impact on the business model. Most notably, Schneider (2018) reviewed the management literature from 2010 to 2016, acknowledging the role of the manager and the importance of change and leadership capability for I4.0 transformation. Similar qualitative reviews on I4.0 management focused on capturing developments at the single firm level (Piccarozzi, Aquilani and Gatti, 2018) or included only small and medium businesses (Moeuf et al, 2017; Ghobakhloo et al, 2022). Lastly, studies reviewed critical success factors (Sony and Naik, 2019) and maturity models for I4.0 (Jesus and Lima, 2020; Dikhanbayeva et al, 2020). However, the above reviews in the realm of management mostly examine general I4.0 requirements for planning, while other organisational implications and business needs such as I4.0 implementation are overlooked.

In response, some reviews have focused more comprehensively on the organisational management aspect at a more granular level. For instance, past studies have reviewed the scope of the I4.0 implementation literature from the organisational perspective at multiple levels (Nayernia, Bahemia, and Papagiannidis, 2022). Similar reviews highlight strategy and organisational change for digital transformation (Hanelt et al, 2021). Likewise, reviews have tried to understand organisational tensions during implementation (Dieste, Sauer, and Orzes, 2022) and understand I4.0 as an organisational strategy for recovery from the Covid-19 pandemic (Ardolino et al, 2022; Ardolino, Bacchetti, and Ivanov, 2022). Similarly, Matt et al,

(2022) reviewed industrial digitalization and clarified organisational path dependency tensions and business ethics, while Cugno, Castagnoli and Büchi, (2021) reviewed such tensions between organisations in international business.

In addition to the above, reviews investigated I4.0 from the socio-technical research perspective (Erro-Garces, 2019; Simões et al, 2022) and the human element, for instance, the implications of human-robot collaboration in manufacturing (Davies, Coole and Smith, 2017). Other reviews included the impact on the larger society, most notably environmental sustainability. For instance, Piccarozzi et al, (2022) reviewed sustainability pillars and I4.0, reinforcing the notion of human resource integration with I4.0 technology as a source of sustainability. Other studies on I4.0 and sustainability reviewed the roadmap (Ching et al, 2021) and framework for emission reduction (Kamble, Gunasekaran, and Gawankar, 2018). In addition, sustainability along the supply chain has been reviewed (Birkel and Müller, 2021) to consider the dynamics of production networks.

In contrast to the growing literature above, the number of operation-centric reviews on I4.0 that reveal granular and often important details applicable to sub-unit levels at the organisation has been reviewed less. In this context, reviews have analysed lean thinking (Bittencourt, Alves, and Leão, 2021), lean Six Sigma 4.0 (Antony et al, 2022), and combining lean and agile practices in manufacturing (Ding, Ferras Hernandez, and Agell Jane, 2023). Also, past I4.0 studies reviewed the performance of supply chains (Rad et al, 2022) and the risks associated with supply chains (Pandey, Singh, and Gunasekaran, 2021). In this growing field, Núñez-Merino et al, (2020) underscore the impact of technology implementation on lean supply chains (Rossini, Powell, and Kundu, 2022) and agile supply chain management (Reyes, Mula, and Díaz-Madroñero, 2023). Other reviews used natural language processing to analyse the impact of I4.0 on multitier supply chains (Zhou, Awasthi, and Stal-Le Cardinal, 2021).

Granular aspects such as the operational level related more to the factory or plant subunit has been even less explored by past reviews. Most notably, Xu, Xu and Li (2018) examined both the technical and operational perspectives on implementation, focusing on the smart factory environment. In addition, reviews investigated smart production planning and control and operations management in the context of I4.0 (Ivanov et al, 2021; Bueno, Godinho Filho and Frank, 2020). Similarly, Lohmer and Lasch (2021) reviewed production planning and scheduling for production networks and organisations with multiple factories implementing I4.0 technology. These reviews more closely examine the smart factory concept from the operational management perspective. Reviewing the past decade of I4.0 literature indicated major research limitations regarding production aspects and considering in parallel the product, marketing, data, the supply chain, and the workforce (Meindl et al, 2021).

### *2.3.2 Text mining and Clustering Results*

This section examines the results of the text and data mining of the full text of the selected articles on I4.0 implementation according to the third step of the review process (section 2.2.3). The keyword frequency of the top 50 results is shown in table 1, including the number of cases (articles) in which the keyword occurs and the TF*IDF representing the uniqueness or rarity of the keywords. The higher the TF*IDF the more a specific keyword is referred to but in a smaller batch of cases.

*Table 1 Keyword in the corpus sorted by frequency.*

| Keyword | FREQ | No. CASE | TF*IDF |
|---|---|---|---|
| INDUSTRYF (I4.0) | 4096 | 94 | 55.9 |
| COMPANY | 3299 | 93 | 60.3 |
| PRODUCT | 1175 | 89 | 43.9 |
| MODEL | 1020 | 86 | 53.3 |
| PERFORMANCE | 954 | 74 | 112.1 |
| ORGANISATION | 914 | 85 | 52.4 |
| SME | 780 | 34 | 355.1 |
| CUSTOMER | 756 | 83 | 51.2 |
| DESIGN | 744 | 79 | 66.3 |
| CHALLENGE | 742 | 84 | 46.4 |
| SERVICE | 725 | 81 | 56.8 |
| RESOURCE | 687 | 82 | 50.1 |
| FACTOR | 625 | 81 | 48.9 |
| EMPLOYEE | 620 | 69 | 91.7 |
| DIGITAL | 586 | 80 | 49 |
| INTEGRATION | 558 | 77 | 56 |
| INNOVATION | 553 | 69 | 81.8 |
| CASE | 552 | 73 | 68.1 |
| IMPACT | 548 | 80 | 45.9 |

| Keyword | FREQ | No. CASE | TF*IDF |
|---|---|---|---|
| ORDER | 515 | 78 | 48.8 |
| RELATIONSHIP | 513 | 69 | 75.9 |
| KNOWLEDGE | 489 | 76 | 51.8 |
| COMPETENCY | 487 | 42 | 177 |
| SUPPLYCHAIN | 475 | 60 | 99.1 |
| APPLICATION | 471 | 77 | 47.2 |
| ADOPT | 438 | 73 | 54.1 |
| DIGITALISATION | 420 | 56 | 100.2 |
| BARRIER | 414 | 45 | 138.1 |
| CAPABILITY | 411 | 62 | 79.9 |
| EFFECT | 409 | 59 | 88.3 |
| ROLE | 404 | 73 | 49.9 |
| CONTEXT | 403 | 66 | 67.4 |
| SOLUTION | 395 | 72 | 51.1 |
| SECTOR | 389 | 66 | 65.1 |
| LEAN | 386 | 28 | 208.3 |
| TOOL | 383 | 73 | 47.3 |
| MATURITY | 380 | 30 | 193.7 |
| ACTIVITY | 361 | 68 | 55.7 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| SUSTAINABILITY | 546 | 57 | 126.1 | MANUFACTURER | 348 | 47 | 109.5 |
| PRACTICE | 539 | 77 | 54.1 | COUNTRY | 339 | 66 | 56.7 |
| PROJECT | 536 | 53 | 140.7 | INFLUENCE | 339 | 61 | 68.3 |
| IOT | 529 | 43 | 186.9 | IMPROVEMENT | 337 | 69 | 49.8 |
| NETWORK | 523 | 74 | 61.5 | CHAIN | 336 | 68 | 51.8 |
| ORGANISATIONAL | 520 | 71 | 70.5 | EXPERT | 335 | 51 | 93.5 |

The results of the text mining revealed five streams of research and the keywords used in the clustering. More importantly, the quantitative results show a high coherence or relatedness of the keywords and the research streams. The five streams of research on I4.0 include the study of (a) Drivers and barriers to implementation, (b) smart factory implementation practices such as 'LEAN' (TF*IDF of 208.3), as well as other technology and system-based resources, such as 'IOT' (TF*IDF of 186.9), showing the widespread use of these keywords throughout the selected studies.

### *2.4 Industry 4.0 Implementation Literature*

Based on the text mining analysis results, eleven distinct streams of research related to the implementation of I4.0 have been identified and are further explained below. The eleven streams of research within the literature on *"industry 4.0 implementation"* is represented across five broad levels, namely industry and firm, smart factory, data, human resource, and supply chain. Table 2 lists the streams of research and presents relevant descriptive and analytic information, such as the coherence, frequency, and number of cases (throughout the corpus) of keywords, clustered into eleven streams within five main levels.

*Table 2 Clustering of I4.0 Literature Streams*

| LEVEL | STREAM | DESCRIPTION | KEYWORDS | COHERENCE | FREQUENCY | NO. CASES |
|---|---|---|---|---|---|---|
| INDUSTRY & FIRM | **INDUSTRY**<br><br>**DRIVERS & BARRIER** | Examining the relevance of implementing I4.0 within the larger regional & industry context | DRIVER; RELEVANT; BARRIER; GLOBALISATION; PERCEIVE | 0.374 | 1814 | 94 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | **ORGANISATIONAL ENABLERS OF I4.0** | Investigating the effect of organisational I4.0 enablers | NEGATIVE; EFFECT; POSITIVE; ACCEPTANCE; POSITIVE EFFECT; EFFECT MANUFACTURING COMPANY; CHALLENGES REGARD | 0.362 | 413 | 59 |
| | **ORGANISATIONAL READINESS & MATURITY** | Using models & tools to assess the organisational readiness for practising I4.0 based on level of maturity | MATURITY; ASSESSMENT; MODEL; READINESS; FOCAL; MATURITY MODEL; MATURITY ASSESSMENT; INDUSTRYF MATURITY; MATURITY LEVEL; DIGITAL MATURITY | 0.335 | 883 | 85 |
| **SMART FACTORY** | **I4.0 TECHNOLOGIES & FACTORY ENABLERS** | Identifying & grouping I4.0 enabling technologies & describing the determinants for adoption at the factory | IDT; SMARTMANUFACTURING; DETERMINANT; KNOWLEDGE COMPETENCY; ADOPT SMIDT | 0.356 | 632 | 38 |
| | **EFFECT ON FACTORY PERFORMANCE** | Studying the indicators & effect of I4.0 on the operational and financial performance | PERFORMANCE; OPERATIONAL; FINANCIAL; IMPROVEMENT; LEAN; LEANPRODUCTION; BUSINESS PERFORMANCE; LEAN PRACTICES; PERFORMANCE INDICATORS | 0.360 | 992 | 84 |
| | **EFFECT ON FACTORY SUSTAINABILITY** | Describing the indicators & effect of I4.0 on factory, environmental and social sustainability | GUIDELINE; ERP; STEPS ACTIVITIES; SUSTAINABILITY ASPECTS; ENVIRONMENTAL SUSTAINABILITY; IMPLEMENTATION GUIDELINES | 0.373 | 529 | 52 |
| **DATA** | **BIG DATA ANALYTICS** | Examining data ecosystem for collection, transfer, storage & analytics using IoT/BDA | BIGDATA; ANALYTICS; IOT; BDA; BIGDATA ANALYTICS; IOT ECOSYSTEM; BDA SCM | 0.351 | 266 | 42 |
| | **CLOUD** | Researching data mobility & decentralised accessibility | CLOUD; HYBRID; PRIVATE; PUBLIC; LAYER; IAAS LAYER; SUPPLYCHAIN NETWORKS | 0.342 | 514 | 66 |
| **HUMAN RESOURCE** | **JOB PROFILES & COMPETENCY** | Investigating new job profiles, new skills & competency requirements for employees and the future workforce | JOB; COMPETENCY; PROFILE; SKILL; EMPLOYEE; KEY COMPETENCY; COMPETENCY MISMATCH; JOB PROFILE; COMPETENCY DEVELOPMENT; COMPETENCY MODEL; COMPETENCY REQUIREMENTS | 0.365 | 724 | 72 |
| **SUPPLY CHAIN** | **HORIZONTAL INTEGRATION** | Examining the links of I4.0 and supply chain partners & stakeholders | PRODUCT; CUSTOMER; SUPPLY; CUSTOMER USERS; EPR; PRODUCT DESIGN; PRODUCT LIFE CYCLE; PRODUCT DEVELOPMENT | 0.333 | 603 | 57 |
| | **RECYCLING & RE-MANUFACTURING** | Describing I4.0 enabled recycling and reuse of products and the relation of I4.0 to the circular economy | EEE; WEEE; REMANUFACTURE; RECYCLING; | 0.348 | 180 | 9 |

### *2.4.1 Level 1: INDUSTRY AND FIRM*

Stream 1: Industry and Drivers and Barriers

In the transformation towards Industry 4.0 (I4.0) adoption, the driving forces exhibit a complex interplay set by the diverse landscape of government policies and regulations across regions and countries (Singhal, 2020). Extensive research efforts have been dedicated to elucidating the nuanced dynamics of I4.0 adoption, recognising its relative significance within the broader industrial sector of regional and country-specific dimensions (Pessot et al, 2021).

This multifaceted exploration of I4.0 adoption unfolds into two distinct streams, meticulously examining both the socioeconomic drivers and barriers at the national and industry level. The literature has to some extent clarified the intricate web of internal drivers and barriers within individual organisations. Conceptual studies have consistently affirmed the overwhelming benefits of I4.0, although they also acknowledge the risks, often shrouded in unpredictability within the realm of management (Mohamed, 2018; Sanghavi, Parikh and Raj, 2019). Consequently, addressing these contemporary challenges, particularly in the context of Lean practices, while navigating the intricate terrain of I4.0 complexities according to regulations, emerges as a formidable hurdle for many small and large enterprises alike (Sanders, Elangeswaran and Wulfsberg, 2016).

At the macro-level of countries, the body of research comprises abstract studies delving into the socioeconomic benefits and common enablers of I4.0. A focal point revolves around the pivotal role played by regional governments in supporting organisations' I4.0 endeavours. This is often through avenues like financial backing (Grenčikova, Kordoš and Sokol, 2019), favourable interest rates (Kohnova, Papula and Salajova, 2019), and industry-specific subsidies (Lin et al, 2018). The discourse also in part extends to encompassing the multifaceted impact of I4.0 on the social, cultural, and economic facets of countries. Studies meticulously examine the influence of *"Lean"* practices on I4.0 implementation within countries characterized by divergent socioeconomic contexts (Hotrawaisaya et al, 2019; Tortorella et al, 2019). Studies also probe the readiness levels of nations (Ślusarczyk, 2018; Grenčikova, Kordoš and Sokol, 2019; Saengchai and Jermsittiparsert, 2019). These investigations firmly establish the common enablers and risks encountered by both industrialised and developing nations.

Furthermore, a significant spotlight is cast on the financial management and strategies required to finance prospective I4.0 initiatives, a formidable challenge faced by investors and entrepreneurs, particularly in developing nations (Alekseev et al, 2018). Additionally, several studies offer comprehensive overviews of communication and resource-sharing practices across multiple firms via Cyber Industry Networks (CIN), highlighting challenges such as low employee skill levels and an overall *"lack of climate for investment in new technologies"* as substantial barriers to I4.0 (Saniuk, S. Saniuk, A. 2018).

Conversely, survey-based research within this domain delivers a more granular analysis by comparing firms of various sizes and sectors across developed and developing economies. Notably, practices like Lean Automation (LA) emerge as precursors to I4.0 implementation in both the Brazilian and Italian manufacturing sectors (Tortorella and Fettermann, 2017; Tortorella et al, 2019). In this context, LA is widely perceived as the result of integrating Lean Production (LP) practices, such as waste reduction, enhanced productivity, and improved quality aligned with customer requirements, with I4.0 technology. Empirical evidence reinforces the positive impact of practising LP and I4.0 on operational performance, although it is more prominently observed in developed nations, where a robust behavioural and process foundation complements technological innovations (Tortorella et al, 2019).

As the research delves deeper, survey studies among Small and Medium-sized Enterprises (SMEs) unveil distinct drivers and barriers that smaller firms within developing nations have experienced. For example, questionnaires administered to Nigerian and Malaysian SMEs underscore the role of information access and cost reduction through advanced technology adoption as enablers of I4.0 implementation. However, this surge in technology adoption also contributes to reluctance and a lack of incentive for adoption, a significant but seldom deeply explored challenge within the literature (Salimon et al, 2019). Similar surveys conducted among SMEs in Iran, Malaysia, and Thailand confirm that I4.0 implementation remains a daunting task for smaller enterprises, despite the reduced cost of Information and Digital Technologies (IDT), such as Artificial Intelligence (AI), and increased accessibility of existing off-the-shelf technologies (Ghobakhloo and Ching, 2019). This challenge primarily stems from a lack of comprehension regarding IDT requirements, affordance, and constraints (Ślusarczyk, Haseeb and Hussain, 2019; Haseeb et al, 2019). However, the SME sector holds the promise of significant performance enhancements due to high leverage, agile responsiveness, and competitiveness (Rauch, Dallasega and Unterhofer, 2019).

In stark contrast, larger enterprises exhibit a greater probability of successfully implementing I4.0, primarily due to reliance on diverse and often replenishable resource pools. For instance, within the Chinese manufacturing sector, larger firms boast a 9.8% higher likelihood of adopting I4.0 technology (Lin, Wu and Song, 2019). Other surveys encompassing East and Central Europe identify similar enablers, such as technology knowledge and the ability of these technologies to strengthen production, products, and services (Tortorella and Fettermann, 2017; Tortorella et al, 2019). These findings emphasize the significance of resource availability and knowledge in the I4.0 adoption journey.

The challenges faced by larger companies extend beyond mere perception or willingness to implement advanced production technology. Specifically, lean management, knowledge networks, and resource management emerge as key facilitators for large firms venturing into implementing I4.0 (Zangiacomi et al, 2020). Despite these valuable insights, the literature still lacks a comprehensive examination of production networks, especially those comprising interconnected sites across diverse geographical locations. In this context, empirical studies investigating interconnected factories embarking on I4.0 implementation reveal a high willingness yet a lingering reluctance to adopt costly technology in the absence of a concrete understanding of the benefits (Ingaldi and Ulewicz, 2020; Pessot et al, 2021; Vrchota et al, 2021). Furthermore, research by Barbieri et al, (2018) sheds light on the concept of "*reshoring*" - the repatriation of production lines - as a catalyst for technological innovation and traceability in contrast to offshoring. However, the literature scarcely delves into the risks and challenges associated with large-scale "*repatriation of production*", particularly within the context of multinational firms and Original Equipment Manufacturers (OEMs) with dispersed geographical facilities.

Stream 2: Organisational Enablers of I4.0

Within the second stream of research, which delves into the organisational enablers of Industry 4.0 (I4.0) implementation, a comprehensive review of various industry and firm challenges associated with this transformative process was conducted. These studies shed light on several crucial aspects that shape the landscape of I4.0 adoption within organisations.

One notable facet pertains to the impact of I4.0 on organisational structures. Research underscores the role of I4.0 in flattening traditional organisational hierarchies (Jerman, Pejić

Bach and Aleksić, 2020), thereby extending the span of control and necessitating a demand for leadership and digital change expertise (Johansson et al, 2019). This evolving landscape may also lead organisations to consider the spin-off of specific business units to enhance agility across various departments (Veile et al, 2019). However, an intriguing avenue for future research arises regarding whether new I4.0 teams, departments, or business units are formed or made redundant because of these structural and cultural changes.

Effective communication and information access emerge as pivotal organisational enablers. Beyond conventional corporate communication methods, such as internal social media (Hauer, Harte and Kacemi, 2018), the level of information accessibility plays a critical role in fostering alignment (Salimon et al, 2019). High-level information sharing not only enables the dissemination of performance improvement data (Robert, Giuliani and Gurau, 2022) but also expedites the sharing of *"soft resources"* like documents and software (Wagire, Rathore and Jain, 2020). It is essential to note that while resource sharing is crucial, it must be regulated effectively to mitigate cybersecurity risks (Raj et al, 2020).

The organisational culture of a firm is another cornerstone of successful I4.0 implementation. Cultivating a culture of innovation (Barata, Rupino Cunha and Coyle, 2020) not only nurtures an internal environment conducive to I4.0 adoption (Wagire, Rathore and Jain, 2020; Bag, Gupta and Kumar, 2021) but also equips organisations to surmount regional social-cultural barriers (Kumar, Vrat and Shankar, 2021). Attributes like openness and a willingness to embrace change are instrumental in fostering information sharing (Pfeiffer, Lee and Held, 2019) and influencing the knowledge development process (Kohnová, Papula and Salajová, 2019). Studies further highlight the point that the successful introduction of new I4.0 communication technologies hinges on the initial reconfiguration of both organisational culture and structures (Ślusarczyk, Haseeb and Hussain, 2019; Cimini et al, 2020).

Absorptive capacity and open innovation have gained prominence to overcome the rigidity of organisational structures and culture, as well as to address the scarcity of Information and Communication Technology (ICT) resources. For instance, Yu and Schweisfurth (2020) emphasize the role of absorptive capacity in enhancing an organisation's capability to sense, evaluate, and learn from external sources of information during ICT implementation. Furthermore, open innovation practices foster resource acquisition by involving end-users and customers at the manufacturing stage (Gerlitz, 2015; Prause, 2015; Pfeiffer, Lee and Held, 2019), with relevance to Small and Medium-sized Enterprises (SMEs) (Prause, 2015). However, an intriguing research gap exists regarding the balance of openness (Himang et al, 2020) and the degree of indigenous Research and Development (R&D) as the implementation journey unfolds.

In a similar vein, the effective implementation of sharing technologies (Chiarini, Belvedere and Grando, 2020) facilitates active resource sharing and paves the way for the exploration of new services and revenue streams (Calabrese, Levialdi Ghiron and Tiburzi, 2021). This resource sharing often acts as a precursor to the exploitation of value propositions through parallel innovation in both technology and management. The reconfiguration of tangible and intangible resources under varying business conditions stands out as a critical aspect of I4.0, especially within the underexplored realm of Socio Technical Systems (Sony and Naik, 2019; Pollak et al, 2020). It is worth noting that only one study was found to explore the concept of dynamic capabilities as a strategy for navigating resource reconfiguration scenarios (Bag, Gupta and Kumar, 2021).

Stream 3: Organisational Readiness and Maturity

Within the third stream of research, which delves into the organisational readiness and maturity required for successful Industry 4.0 (I4.0) implementation, a comprehensive review was conducted. This stream emphasizes the need for firms not only to identify organisational and industry enablers but also to thoroughly assess their readiness and maturity levels when embarking on the I4.0 journey. The literature distinguishes between readiness assessments and maturity models, offering valuable tools for managers and practitioners navigating this transformative process.

Assessing a firm's preparedness to implement I4.0 is considered a crucial step in the digitalization process, and empirical studies in this area are relatively scarce. For instance, Črešnar et al, (2020) conducted a survey that empirically highlighted the significance of traditional management tools like balanced scorecards and customer segmentation as pivotal readiness factors. Other studies explored readiness through the lens of systems thinking (Simetinger and Zhang, 2020) or explored the legal aspects of preparedness (Wagire, Rathore and Jain, 2020; Kumar, Vrat and Shankar, 2021). While readiness assessments are recognized as valuable, they are still an underexplored area within the literature.

In contrast, I4.0 maturity models (MM) have garnered more attention due to their practical applicability. These models serve as guidelines and tools for managers, aiding in the development of frameworks and roadmaps for organisational change (Liebrecht et al, 2021). Studies comparing I4.0 maturity models have identified logical dependencies that have to be addressed, often referred to as *"breaking points"*, to advance to higher levels of I4.0 maturity (Simetinger and Zhang, 2020). Notably, recent research has expanded the scope of maturity indicators beyond smart factories and I4.0 technologies, encompassing organisational factors, people, culture, and strategic measures (Bibby and Dehe, 2018; Wagire, Rathore and Jain, 2020; Vuksanović Herceg et al, 2020). However, the measurement of implementation levels based on management indicators, such as decision-making, resource allocation, strategy, and policy formulation, has been relatively less explored (Himang et al, 2020).

At the strategic level, additional drivers and barriers come to the fore. Business Model Innovation (BMI) has emerged as a pivotal driver for I4.0 implementation, serving as a catalyst for stakeholder consensus, bolstering manufacturing sustainability, and functioning as a tool to materialize new value propositions and revenue streams (Birkel et al, 2019; Müller 2019; Tarifa-Fernández, Sánchez-Pérez and Cruz-Rambaud, 2019).

The maturation process of manufacturers adopting I4.0 significantly influences how I4.0 is measured and how the business model evolves. For instance, the degree of implementation and the actual delivery methods are intricately interconnected (Butt, 2020). This realization has spurred the need for standardized implementation protocols, alignment, and governance to effectively determine key performance indicators (KPIs), key risk indicators (KRIs), and process performance indicators (PPIs). These indicators encompass dimensions like cost, time, quality, employee factors, and flexibility (Liebrecht et al, 2021), with a focus on single business units (Pessot et al, 2021). Implementation, however, extends beyond process management, encompassing areas like production planning and control, logistics, supply chain management, cybersecurity, and customer support (Narula et al, 2020).

To navigate this intricate landscape, the implementation of pilot projects has emerged as a valuable strategy, serving as a reversible test environment that minimizes disruptions to regular operations (Butt, 2020). These pilot initiatives have been linked to increased levels of research and development (R&D) (Lin, Wu and Song, 2019), enabling the identification of project-specific budget and resource requirements (Prause, 2015; Veile et al, 2019). Moreover, early-stage technology implementation benefits from guided *"exploration* *projects"* and pilot programs, which involve limited investments to facilitate integration and leverage challenges to drive innovation and scalability (Ghobakhloo, 2020b).

### *2.4.2 Level 2: SMART FACTORY*

Stream 4: Industry 4.0 Technologies

Enabling technologies play a pivotal role in driving the successful implementation of Industry 4.0 (I4.0). In this section, we offer a brief overview, albeit not the primary focus of this review, of the technological foundations of I4.0 at the smart factory level. We categorize these technologies into two main groups: Information and Digital Technologies (IDT) and Manufacturing Technologies.

Within the first group, there is an array of implementation techniques for IDTs. Notably, the Internet of Things (IoT) and Big Data Analysis (BDA) bolster an organisation's data capabilities by enhancing communication protocols for heterogeneous devices (Rajput and Singh, 2018) and improving predictive analytics for customer needs in technology and manufacturing sectors (Oncioiu et al, 2019). Artificial Intelligence (AI), neural networks, and machine learning are closely associated with I4.0 implementation and have proven to be invaluable tools for enhancing factory planning and logistics (Rakyta et al, 2016; Ellefsen et al, 2019). For instance, neural-pseudo networks have been demonstrated to enhance production planning, augmenting existing IT systems, while machine learning contributes to predictive maintenance and optimal production conditions (Ellefsen et al, 2019; Rauch, Dallasega and Unterhofer, 2019; Konur et al, 2021). High-performance computing is another critical element that complements data-intensive technologies (Ghobakhloo and Ching, 2019; Calabrese, Levialdi Ghiron and Tiburzi, 2021) and enhances simulation capabilities (Urban, Łukaszewicz and Krawczyk-Dembicka, 2020), facilitating activities such as virtual testing (Narula et al, 2020) and discrete event simulation (Ghafoorpoor Yazdi, Azizi and Hashemipour, 2019). Virtual and augmented reality (AR/VR) technologies further enrich the manufacturing landscape, offering services for both users and clients (Pech and Vrchota, 2020; Ramírez-Durán et al, 2021).

However, the increasing mobility and decentralization of technologies has also led to heightened cybersecurity risks. Measures to mitigate these risks include data protection strategies (Stentoft and Rajkumar, 2020), read-only access to production control data (Konur et al, 2021), and the utilization of Blockchain technology (Bibby and Dehe, 2018; Wagire, Rathore and Jain, 2020). Cybersecurity is acknowledged as a prerequisite for implementing other I4.0 IDT technologies (Yu and Schweisfurth, 2020; Calabrese, Levialdi Ghiron and Tiburzi, 2021). Additionally, existing technologies like the Manufacturing Execution System and enterprise resource planning serve as reliable foundations for the integration of more advanced technologies (Bibby and Dehe, 2018; Sader Husti and Daroczi, 2019; Ghobakhloo and Ching, 2019). Cloud computing capabilities further enhance big data analytics, facilitating real-time connectivity and traceability across supply chains (Bibby and Dehe, 2018) and promoting cloud manufacturing (Calabrese, Levialdi Ghiron and Tiburzi, 2021), while also contributing to cybersecurity through the development of cloud policies (Pessot et al, 2021).

The growing maturity, accessibility, and affordability of present manufacturing technologies also pave the way for I4.0 implementation. Advanced sensors, for instance, are widely utilized for data collection (Magalhaes et al, 2020; Pech and Vrchota, 2020) but continue to undergo efficiency improvements (Sanghavi, Parikh and Raj, 2019). Autonomous robots are deployed in product development and production (Stentoft and Rajkumar, 2020; Yu and Schweisfurth, 2020), often necessitating factory layout adjustments (Chiarini, Belvedere and Grando, 2020). Controllers such as PLC, DCS, and SCADA monitor production and provide critical alerts (Rakyta et al, 2016; Ghobakhloo and Ching, 2019), enabling necessary corrective actions (Konur et al, 2021). Automated guided vehicles contribute to shop-floor transportation automation and expedite material handling (Rakyta et al, 2016; Sanghavi, Parikh and Raj, 2019). In contrast to subtractive manufacturing, additive manufacturing, including 3D printing, has gained prominence in reducing inventory (Turner et al, 2019), facilitating rapid prototyping (Wagire, Rathore and Jain, 2020; Pech and Vrchota, 2020), and enabling customization (Devi et al, 2020). Lastly, computer-aided design (CAD) tools and computer numerical control (CNC) machines serve as foundational technologies, streamlining technological documentation flow during production (Urban, Łukaszewicz and Krawczyk-Dembicka, 2020) and aiding in visualizing products and the production process (Ramirez-Duran et al, 2021).

While our review provides descriptive insights into the broad range of technologies integral to I4.0 implementation, there remains a lack of understanding regarding the decision-making processes surrounding technology acquisition from suppliers or in-house development, particularly in terms of protecting intellectual property and mitigating knowledge misappropriation risks. Furthermore, the literature is less extensive when it comes to elaborating on strategies for value protection during I4.0 implementation, an essential consideration from an organisational perspective (Teece, 2018).

Lean practices, including Lean Six Sigma (Sony, 2020), have been extensively discussed as effective strategies for implementing the smart factory (Sjödin et al, 2018) and Lean and Agile production methodologies have emerged as key facilitators in the adoption of Industry 4.0 (I4.0) principles (Chiarini, Belvedere and Grando, 2020). Remarkably, these approaches have proven to be valuable across a range of socio-economic conditions and firm sizes, highlighting their adaptability and universal applicability (Tortorella and Fettermann 2017; Tortorella et al, 2019). Even within developed nations, the integration of Lean practices has been recognized as a robust foundation that complements technological advancements and fosters continuous improvements (Tortorella et al, 2019).

Lean and Agile strategies are particularly crucial for larger firms (Zangiacomi et al, 2020), where they streamline implementation processes and strike a balance between organisational efficiency and effectiveness. Similarly, these strategies prove invaluable for Small and Medium-sized Enterprises (SMEs) by simplifying their journey towards I4.0 adoption (Cimini et al, 2020). In this context, I4.0 implementation owes its success not only to Lean practices applied within organisations but also to their extension into customer and supplier relationships (Hotrawaisaya et al, 2019). Furthermore, Lean Manufacturing (LM) and Lean Production (LP) principles play a pivotal role in optimizing processes and promoting the utilization of I4.0 technologies (Sanders, Elangeswaran and Wulfsberg, 2016; Rosin et al, 2019; Ghobakhloo and Fathi 2019).

These elements, such as Just-In-Time systems, Jidoka, and Heijunka, enhance process efficiency while facilitating the integration of I4.0 innovations (Rosin et al, 2019; Ghobakhloo and Fathi, 2019). Additionally, Lean Manufacturing contributes to the readiness level required for successful I4.0 implementation (Črešnar et al, 2020). Lean Production emphasizes the technological facets of lean practices, including Human-Computer Interaction (HCI), production optimization, and reconfigurability (Jiwangkura et al, 2020). The Lean culture has been instrumental in guiding the organisational restructuring necessitated by the adoption of new technologies (Cimini et al, 2020). Lean and Agile thinking fundamentally shapes the continuous improvement of factory operations, transcending departmental boundaries and aiming to enhance productivity and customer satisfaction (Sader, Husti and Daroczi, 2019; Saabye et al, 2020; Raj et al, 2020; Črešnar et al, 2020).

In addition to Lean practices, standardization (e.g., device, process, communication) and the appropriateness of infrastructure have emerged as critical enablers for smart factories (Rajput and Singh, 2018; Birkel et al, 2019; Pfeiffer, Lee and Held, 2019). Standardization not only enhances competitiveness but also bolsters cybersecurity and fosters interoperability, ultimately facilitating vertical integration (Müller et al, 2018; Singh and Bhanot, 2019; Sanghavi, Parikh and Raj, 2019; Konur et al, 2021).

The integration of I4.0 technologies within smart factories heavily relies on technology competency and seamless integration, especially for SMEs that leverage I4.0 technologies within their core competencies (Yu and Schweisfurth 2020). Proficiency in Information and Digital Technologies (IDT) knowledge expedites the adoption of digital technologies, thereby accelerating smart manufacturing information and I4.0 implementation (Ghobakhloo and Ching 2019). Retrofitting, while complex, is a valuable approach for reducing implementation costs (Birkel et al, 2019). Competency studies that define firms' ability to reconfigure factory resources through Dynamic Capability have been conducted, shedding light on the role of expertise in successful implementation (Bag, Gupta and Kumar, 2021). However, research on the transformation of legacy systems within traditional factory settings remains limited, warranting further exploration (Ramírez-Durán et al, 2021; Konur et al, 2021).

Finally, a subset of studies has explored the harmonization of smart factories with their logistical components. The integration of I4.0 technologies has been identified as a means of bridging the gap between logistics enterprises' performance and shared knowledge and communication, benefiting both inbound and outbound logistics (Ślusarczyk, Haseeb and Hussain, 2019; Vuksanović Herceg et al, 2020). Additionally, investigations into Artificial Intelligence (AI) for logistics, automated guided vehicles, and autonomous mobile robots have contributed to enhancing the efficiency of logistical operations within the smart factory (Ellefsen et al, 2019; Rakyta et al, 2016; Chiarini, Belvedere and Grando, 2020).

### Stream 5: Effect of Industry 4.0 on Factory Performance

Our comprehensive analysis has revealed numerous productivity-related benefits stemming from I4.0 implementation. Notably, the adoption of paperless manufacturing and order visualization has been associated with a commendable reduction in production costs (Liebrecht et al, 2021). Furthermore, the incorporation of e-value chains is geared towards the reduction of lead times, subsequently leading to the minimization of inventory costs (Bibby and Dehe, 2018). Real-time analysis enhancements have the potential to elevate production performance by a notable 10% (Saabye, Kristensen and Wæhrens, 2020). In a similar vein, the utilization of cloud-operated hybrid supply chain models has demonstrated the capacity to achieve substantial savings of up to 30% through streamlined and lean ordering and supply delivery processes (Sundarakani et al, 2019).

Programmable manufacturing advisors have emerged as invaluable tools for providing managers with insights into issues related to bottlenecks, settling time, and lead time (Alavian et al, 2020; Ramírez-Durán et al, 2021). Semi-autonomous systems, employing monitoring, virtualization, and visualization of factory operations, effectively address throughput losses, which often result in overtime (Alavian et al, 2020). Additionally, the integration of rapid prototyping methodologies has been instrumental in enhancing production agility (Rauch, Dallasega and Unterhofer, 2019) and stimulating workers' creativity by expanding design possibilities (Črešnar et al, 2020).

Furthermore, the integration of Industry 4.0 principles with customer and supplier processes has proven to be a catalyst for improved information sharing and the dissemination of best practices (Wagire, Rathore and Jain, 2020; Himang et al, 2020). The active involvement of stakeholders has been closely linked to performance improvements across various dimensions, including lead and delivery times, product quality, and logistics costs (Chiarini, Belvedere and Grando, 2020) Leveraging sensors, cloud technologies, and Big Data Analysis (BDA) has paved the way for enhanced product quality and consistency by mitigating the inherent risks associated with manual decision-making (Konur et al, 2021). In this context, the virtualization of a single production line has not only optimized its performance but also served as a blueprint for optimizing other lines and future facilities (Nguyen and Luu 2020). Similarly, the implementation of highly interconnected, albeit energy inefficient IoT ecosystems has yielded significant improvements in manufacturing performance (Ślusarczyk, Haseeb and Hussain, 2019; Singh and Bhanot 2020).

Moreover, empirical time studies conducted over specific time intervals have identified Overall Equipment Efficiency (OEE) as a pivotal benchmark for evaluating manufacturing productivity (Ghafoorpoor Yazdi, Azizi and Hashemipour, 2018; Ghafoorpoor Yazdi, Azizi and Hashemipour, 2019). For instance, linking the availability, performance, and OEE of individual resources, within a system has resulted in a remarkable 10% increase in OEE attributed to I4.0 implementation (Pessot et al, 2021). Additionally, the implementation of preventive maintenance, based on data analysis and serving as an internal service provision prior to equipment failure, has gained increasing prominence (Alavian et al, 2020; Singhal 2020; Konur et al, 2021). This strategic approach effectively curtails machine downtime due to failure, expands the pool of active machines, and augments capacity utilization (Rakyta et al, 2016).

Stream 6: Effect of Industry 4.0 on Factory Sustainability

Beyond the notable gains in production performance, the implementation of Industry 4.0 (I4.0) has demonstrated a remarkable potential for fostering sustainability improvements. Notably, experimental studies have highlighted the pivotal role of sustainable enterprise resource planning (ERP) as a versatile tool for orchestrating the various stages of implementation (initiation, planning, execution, monitoring/control, closure) across multiple organisational levels (Chofreh et al, 2020). In this regard, sustainable ERP has exhibited the capacity to yield substantial reductions in energy consumption and carbon emissions, with potential reductions of up to 40%.

Furthermore, the implementation of I4.0 has been associated with a diverse range of sustainability benefits. Notably, it has been linked to reduced land and water usage (Ghafoorpoor Yazdi, Azizi and Hashemipour, 2018; Ghafoorpoor Yazdi, Azizi and Hashemipour, 2019), decreased energy consumption (Urban, Łukaszewicz and Krawczyk-Dembicka, 2020; Konur et al, 2021), an increased potential for harnessing renewable energy sources (Vrchota et al, 2020; Pessot et al, 2021), and mitigated air emissions (Rajput and Singh 2019a; Narula et al, 2020). However, it is worth noting that in the pursuit of I4.0 implementation, many firms have placed a higher priority on flexibility and automation over sustainability initiatives (Pessot et al, 2021). Although references were made to emissions releases and the carbon footprint of factories, these assertions lacked empirical substantiation (Gerlitz 2015; Birkel et al, 2019; Rajput and Singh 2021).

In contrast, a single study has investigated the reduction of waste leakage and loss, targeting the optimization of technical equipment and machinery operation alongside the enhancement of thermal energy utilization, thereby contributing to both cost reduction and improved sustainability (Vrchota et al, 2021).

### *2.4.3 Level 3: DATA*

Stream 7: Big Data Analytics

In the realm of Big Data Analytics (BDA), the focus is squarely on data management capabilities and requirements, encompassing data collected at various stages, albeit in diverse formats and of varying quality. The adoption of Industry 4.0 (I4.0) thrives on data spanning the entire lifecycle. For instance, the management of data flow, including acquisition, transfer, storage, and analysis, gives rise to novel activities such as data-driven customer services (Ramírez-Durán et al, 2021), internal services like predictive maintenance (Narula et al, 2020), and automated processes like machine-to-machine communication (Müller, 2019; Sanghavi, Parikh and Raj, 2019).

Regarding data collection, embedded devices can *"interact with the surrounding environment and store and share data about their status and usage throughout their entire lifecycle"* (Arcidiacono et al, 2019). However, this necessitates appropriate information bridging technologies such as IoT data infrastructure (Tarifa-Fernández, Sánchez-Pérez and Cruz-Rambaud, 2019; Rajput and Singh, 2018) to reduce the influx of irrelevant information (Sjödin et al, 2018), enhance data consistency (Jiwangkura et al, 2020), and, in certain cases, maintain a post-usage repository of data with product information (Rajput and Singh, 2018).

Few organisations maintain dedicated data management departments, and most data remains unanalysed, it is examined sporadically by employees, or processed by embedded software functions (Pessot et al, 2021). Interestingly, data flow within digital communication networks was relatively high, standing at 67% to 74% in upstream and downstream value chains, with a similar level of digitization across firms (Pessot et al, 2021). Similarly, intra-firm communication has been enhanced through the establishment of web communities and internal social media platforms (Veile et al, 2019). Likewise, the increased availability of mobile technology, agent-based systems, and the improved capabilities of internal wireless networks contribute to decentralized data collection within production lines (Barata, Rupino Cunha and Coyle, 2020). In this context, the Industrial Internet of Things (IIoT) has enriched human-machine and machine-to-machine (M2M) communication (Wilkesmann, M. and Wilkesmann, U, 2018), facilitated by advanced sensors and fast, though not real-time, 5G networks, among other technologies (Ellefsen et al, 2019; Ghobakhloo and Fathi, 2019).

The Internet of Things (IoT) and Big Data Analytics (BDA) serve as prerequisites for large-scale data processing and interpretation, enabling more advanced computational and analytical capabilities, including unstructured data gathering, data formatting, pattern recognition, and predictive analytics (Rajput and Singh, 2018). IoT ecosystems support the service-oriented architecture (SOA), through which vendors and I4.0 providers can offer data-centric logistics and maintenance services via the Internet of Services (IoS) (Wang, X. and Wang, L. 2019; Ślusarczyk and Haque, 2019). Other studies underscore the necessity of addressing cybersecurity and investment concerns, but largely associate BDA with optimizing inventory and asset productivity, as well as achieving faster response times and greater integration across the supply chain (Oncioiu et al, 2019).

Real-time capability, in the context of data management, is integral to implementation, although it remains understudied empirically. Notably, Wagire, Rathore and Jain, (2020) correlate the absence of real-time data capability with low maturity and weak technology integration. Nonetheless, real-time technologies, which can be implemented by third-party partners (Pessot et al, 2021), have been deemed insufficient. Fully harnessing real-time capability necessitates *"second-order problem-solving abilities"* and a supportive learning environment (Saabye, Kristensen and Wæhrens, 2020).

Closed-loop supply chains have the potential to introduce and extend the concept of the digital twin (DT) beyond merely replicating the smart factory itself, enabling the creation of a shared network of manufacturing resources (Rajput and Singh, 2018). DTs are increasingly crucial for visualizing (through BDA and simulation) and controlling operations across multiple complex stages. DTs are defined as *"software representations of assets and processes that contribute to the prediction and optimization of manufacturing performance"* (Ghobakhloo, 2019). Additionally, both experimental (Wang, X. and Wang, L. 2019) and case studies (Gu et al, 2019) of electrical and electronics equipment (EEE) emphasize the significance of a universal DT and the integration of lifecycle data from cradle to grave. Nevertheless, universal

DT propositions remain insufficiently explored in other high-tech sectors, and no DT solution has been identified for low-tech sectors and SMEs. This is partly due to the sensitive nature of production stages, which remain concealed and isolated due to information asymmetry and undefined data sharing boundaries intended to protect intellectual property (IP) (Wang, X. and Wang, L. 2019).

Stream 8: Cloud

In the domain of Cloud computing (CC), there is an alternative to rigid internal infrastructure for data management, and recent research papers have started to explore its significance within the context of Industry 4.0 (I4.0). Cloud technology has gained widespread recognition as a viable solution offering *"on-demand network access to a shared pool of configurable resources" (*Bibby and Dehe, 2018; Sanghavi, Parikh and Raj, 2019; Butt, 2020; Konur et al, 2021). In this context, cloud networks facilitate real-time decision-making for internal services (Bag, Gupta and Kumar, 2021; Konur et al, 2021) and introduce new customer services (Ramírez-Durán et al, 2021), particularly within the realm of Cyber Industrial Networks (Saniuk, S. and Saniuk, A, 2018).

Specifically, cloud computing serves as an effective tool for enabling the implementation of the Industrial Internet of Things by integrating soft resources (Urban, Łukaszewicz and Krawczyk-Dembicka, 2020; Wagire, Rathore and Jain, 2020; Calabrese, Levialdi Ghiron and Tiburzi, 2021). It can also help reduce data clutter, subsequently enhancing simulation capabilities (Simetinger and Zhang, 2020) and improving enterprise resource planning (Ghobakhloo and Fathi, 2019). However, the adoption of cloud storage varies significantly, with studies showing only 8% of SMEs choosing to store data in the cloud (Ingaldim and Ulewicz, 2020). Other studies indicated this to be higher at 20% and 54% of in stark contrast to the 92% adoption rate among large firms (Yu and Schweisfurth, 2020). This disparity is attributed to a lack of expertise and trust (Pech and Vrchota, 2020) and the existence of underexplored security concerns (Bibby and Dehe, 2018; Singh and Bhanot, 2019; Birkel et al, 2019).

Within hybrid cloud networks, cloud brokers serve as intermediaries connecting various departments and functions (Veile et al, 2019; Jiwangkura et al, 2020) for both private internal users and external customers (the public) (Wagire, Rathore and Jain, 2020). For instance, cloud technology facilitates the servitisation of platforms, aligning software and processes with customers, although it is not primarily used as a tool for performance measurement (Chiarini, Belvedere and Grando, 2020). Hybrid cloud platforms, characterized by software sharing across users (referred to as *"multitenancy"*) and service offerings (e.g., Infrastructure as a Service or IaaS), have been found to enhance monitoring and support the servitisation of complex supply chain networks (Sundarakani et al, 2019). Lastly, the cloud enables Just-In-Time processes (Rosin et al, 2019) and digital twins throughout the product lifecycle (Wang, X. and Wang, L, 2019).

### *2.4.4 Level 4: Human Resources*

Stream 9: Job Profiles and Competencies

The human element within the implementation of Industry 4.0 (I4.0) is increasingly gaining attention. The integration of I4.0 is expected to have far-reaching effects on workers and various facets of the work environment (Basir et al, 2019; Grenčikova, Kordoš and Sokol, 2019). This transformation is driven by the growing demand for specific competencies in the context of I4.0 implementation (Barata, Rupino Cunha and Coyle, 2020; Marnewick A. and Marnewick C, 2019; Sony and Naik, 2019). Notably, I4.0 technologies are fostering the emergence of innovative job profiles characterized by increased autonomy, blending technical and non-technical competencies (Cimini et al, 2020).

The adoption of I4.0 technologies is also reshaping work models, with remote or telework altering traditional working time structures (Müller et al, 2018). Moreover, increased monitoring and automation are altering working conditions and patterns (Sanghavi, Parikh and Raj, 2019; Robert, Giuliani and Gurau, 2022), subsequently influencing workplace design (Veile et al, 2019). However, it is important to note that automation is often associated with concerns about job losses and employee resistance to change, which remains a significant implementation challenge (Zangiacomi et al, 2020; Raj et al, 2020). Resistance can hinder the acquisition of new competencies (Ingaldi and Ulewicz, 2020) and impede the acceptance of new technologies like virtual reality (VR), potentially reducing the decision-making and problem-solving competencies of shop-floor workers (Chiarini, Belvedere and Grando, 2020).

In contrast, collaborative robots (Cobots) enjoy wider acceptance, although their use can lead to increased labour-intensive work downstream due to higher throughput (Newman et al, 2021). Resistance is less pronounced among middle managers, who often attribute workforce challenges to a lack of training and management competencies (Vuksanović Herceg et al, 2020). Furthermore, guiding both experienced and new workforces through I4.0 implementation necessitates alignment with a comprehensive human resource strategy (Veile et al, 2019). For example, collaborative training programs for the workforce are associated with enhancing "flexibility to adapt to new roles and work environments" (Kazancoglu and Ozkan-Ozen, 2018), which, in turn, benefits the evolution of the entire smart factory workforce (Sjödin et al, 2018).

Additional studies have explored the changing role of workers from a competency perspective. For instance, promoting team fluidity across production levels (Pfeiffer, Lee and Held, 2019) has been linked to encouraging early employee involvement (Arcidiacono et al, 2019) across diverse industry sectors (Škrinjarić and Domadenik, 2019; Robert, Giuliani and Gurau, 2022). The formation of specialized *"teams of performers"* for high-tech projects (Matyushenko et al, 2019) necessitates specific project management competencies. Particularly, adopting a *"servant-leadership"* style over outdated *"command and control"* strategies has been shown to simplify implementation (Marnewick A. and Marnewick C, 2019; Sony and Naik, 2019; Vuksanović Herceg et al, 2020; Vrchota et al, 2021). In this context, generic competencies transferable to various roles and departments (Škrinjarić and Domadenik, 2019) have proven beneficial. More specifically, soft skills like digital proficiency (e.g., software usage, analytics, etc.) have been widely associated with successful implementation (Raj et al, 2020; Kumar, Vrat and Shankar, 2021). The rising demand for technical skills related to mechatronics, smart system maintenance, process analysis, and bionics not only enhances factory productivity (Jerman, Pejić Bach and Aleksić, 2020) but also the ability to handle traditional analogue production systems (Ingaldi and Ulewicz, 2020). In the early stages of implementation, technical competencies are prioritized over personal or methodological competencies, such as problem-solving and risk management (Cimini et al, 2020).

Additionally, companies are compelled to incentivize and retain their skilled workforce, including programmers (Birkel et al, 2019), by considering internal talent before external recruitment (Zangiacomi et al, 2020). The literature extensively discusses internal and external workforce training as an integral part of I4.0 delivery (Devi et al, 2020; Bag, Gupta and Kumar, 2021). Training should encompass more than just ICT competencies, extending to interdisciplinary knowledge gained through e-learning, scenario-based training, traditional on-the-job instruction, and workshops (Veile et al, 2019; Škrinjarić and Domadenik, 2019). Learning for I4.0 implementation requires a blend of technical training (Arcidiacono et al, 2019) and soft skills. Competencies related to analytics, teamwork, and self-management (Jerman, Pejić Bach and Aleksić, 2020; Pessot et al, 2021) enhance procedural understanding, abstraction abilities, and fault and error recovery skills (Kazancoglu and Ozkan-Ozen, 2018).

Finally, a few studies have focused on worker safety. For example, Human-Machine-Interaction (HMI) necessitates comprehensive considerations of workplace safety beyond legal regulations (Veile et al, 2019). Likewise, addressing human well-being in job design can mitigate occupational health and physical safety concerns (e.g., fatigue, musculoskeletal disorders), psychological health issues (e.g., fairness, stress, motivation), and other secondary effects on human workers. These factors require attention from system designers and I4.0 implementation teams (Neumann et al, 2021).

### *2.4.5 Level 5: Supply Chain Level*

Stream 10: Horizontal Integration

The adoption of Industry 4.0 (I4.0) has been linked to numerous outcomes within the supply chain domain. For instance, several studies have explored modelling tools for enhancing supply chain integration, such as the supply chain operations reference model (Gu et al, 2019). It has also been observed that the implementation of I4.0 can significantly enhance supply chain agility, as evidenced by studies conducted by Oncioiu et al, (2019) and Chiarini, Belvedere and Grando, (2020). Additionally, there is evidence to suggest that it has a somewhat positive impact on supply chain resilience, as demonstrated by Saengchai and Jermsittiparsert (2019).

One notable consequence of supply chain integration facilitated by I4.0 is the potential relocation of facilities closer to customers, aimed at shortening the supply chain and mitigating environmental impact (Rajput and Singh, 2018; Wang, X. and Wang, L. 2019). Furthermore, research has delved into the various phases of the customer lifecycle, particularly the discovery and shopping phases, as well as the use and service phase, within the context of small and medium-sized enterprises (SMEs) utilizing client applications integrated with manufacturing processes (Ramírez-Durán et al, 2021). Such integration has the potential to enhance the rate and accuracy of continuous and agile customer feedback regarding product quality (Ghobakhloo and Fathi, 2019), thus helping with the better definition of customer requirements (Barata, Rupino Cunha and Coyle, 2020).

Moreover, the level of integration among factories, suppliers, and customers has the potential to create intricate digital and interdependent industrial networks (Saniuk, S. and Saniuk, A, 2018; Veile et al, 2019; Sundarakani et al, 2019). Nonetheless, it is worth noting that SMEs, in particular, exhibit hesitancy in sharing data within supply chains due to concerns over potential loss of bargaining power and data security issues (Arcidiacono et al, 2019; Birkel et al, 2019).

Stream 11: Recycling and Remanufacturing

The utilization of I4.0 technologies to enable the reuse and recycling of resources has been examined within the sustainability framework and the ongoing efforts to advance I4.0 capabilities. For example, some companies have incorporated recycling as part of their after-sales services (Pessot et al, 2021). Furthermore, it has been established that I4.0 enablers play a positive role in moderating the implementation of sustainable manufacturing capabilities (Bag, Gupta and Kumar, 2021). This can be attributed to factors such as product modularity, which reduces disassembly costs (Gu et al, 2019), and the use of digital twins to store data about remanufactured products (Wang, X. and Wang, L. 2019), thereby simplifying the refurbishment and disposal processes associated with remanufacturing.

A broader perspective on the efficient utilization and recirculation of I4.0 material resources is encapsulated in the concept of the Circular Economy (CE). In this context, the implementation of I4.0 is seen as a means of ensuring that *"resources will remain in the closed loop; thus, the life of the resources will increase"* (Bag, Gupta and Kumar, 2021). This extended lifecycle enhances the value of materials, products, and components (Rajput and Singh, 2021), especially for facilities located near customers (Turner et al, 2019).

### *2.5 Industry 4.0 Limitation and future research avenues*

A review of the literature on Industry 4.0 (I4.0) implementation has revealed key research gaps, presenting opportunities for future investigation (Snyder, 2019). As shown in table 3, the text-mining and clustering, in addition to the qualitative review of the eleven streams of research across the five levels, found critical areas left unexplored, while other research streams are increasingly being studied yet warrant additional research.

Four major gaps emerged from the analysis of existing studies. First, it is evident from the literature that most studies explore narrow streams of I4.0 research at a more general firm-level, with limited theoretical and practical implications for I4.0 decision makers. Second, the outcome of implementing I4.0 is still unclear, leaving many firm/factory managers reluctant to engage in I4.0 projects. Third, the requirements other than the I4.0 technology are examined at a very general level, with many important antecedents and enablers remaining hidden. Lastly, the literature on I4.0 implementation is atheoretical, hindering evidence-based research.

*Table 3 I4.0 implementation literature landscape.*

| | | Research Method | | | Level-of-Analysis | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Level | Stream | Conceptual | Survey | Case study | Firm | Factory | Supply Chain | Group/System | Individual/Asset |
| INDUSTRY AND FIRM | Industry Drivers and Barrier | 1 | 14 | 2 | 15 | 1 | 0 | 0 | 0 |
| | Organisational Enablers of I4.0 | 5 | 11 | 11 | 15 | 3 | 0 | 1 | 1 |
| | Organisational Readiness and Maturity | 2 | 6 | 7 | 12 | 2 | 1 | 0 | 0 |
| SMART FACTORY | I4.0 Technology and Factory Enablers | 8 | 22 | 18 | 41 | 13 | 4 | 5 | 6 |
| | Factory Performance | 8 | 14 | 12 | 28 | 8 | 2 | 4 | 4 |
| | Factory Sustainability | 2 | 4 | 2 | 7 | 1 | 0 | 2 | 3 |
| DATA | BDA | 2 | 7 | 7 | 12 | 5 | 2 | 2 | 2 |
| | Cloud | 4 | 5 | 7 | 13 | 3 | 1 | 1 | 1 |
| HR | Job Profiles and Competency | 4 | 17 | 8 | 29 | 6 | 2 | 1 | 6 |
| SUPPLY CHAIN | Horizontal Integration | 1 | 4 | 5 | 7 | 2 | 4 | 0 | 0 |
| | Recycling and Re-Manufacturing | 0 | 1 | 2 | 2 | 1 | 0 | 1 | 2 |

### *2.5.1 Gap 1: Limited Focus on Granular Subunits*

The review of the eleven research streams across five levels indicated the importance of a contingent approach towards digital transformation and successful realisation of the intended goals of implementing I4.0 (Das and Jayaram, 2003; Hendricks and Singhal, 2021). Lack of contingent approaches to investigating I4.0 implementation also resulted in vague and ambiguous strategies for business model innovation (Foss and Saebi, 2017; Kiel, Arnold and Voigt, 2017; Snihur, Amit and Zott, 2021).

Existing research predominantly concentrates on the firm-level, overlooking the nuances, tensions, and paradoxes at more granular organisational sub-unit levels. In fact, the wider literature indicates that market differences particularly affect operational strategy and the factory and not necessarily the entire firm (Berry et al, 1991). This calls for different strategies to be studied to clarify the mechanisms and interdependencies among units of the same business (i.e, factory) and among functions of manufacturing units (Swink, Narasimhan and Kim, 2005; Schoenherr and Swink, 2012). In this context, centralisation of decision making is still vaguely understood. As expected, the number of such studies at the supply chain level is greater but neither vertical nor horizontal integration related studies were found to explore the factory unit-of-analysis. The literature is lacking a clear understanding of how I4.0 is affected by varying degrees of top management support (Arcidiacono et al, 2019), top management readiness (Cinite et al, 2009) and management commitment to maximise IT impact (Quaadgras et al, 2014).

### *2.5.2 Gap 2: Unclear Consequences and Outcome of Adoption*

The literature neglects the above, and more specifically fails to comprehensively explore internal dynamics crucial for I4.0 success (Jacobs, Yu and Chavez, 2016; Gillani et al, 2020; Chen and Wang, 2022). The current literature in large part fails to address how factors like cross-functional integration (Swink, Narasimhan and Kim, 2005), internal communication, and alignment impact I4.0 implementation. Empirical evidence is increasing, yet the technology in focus is on specific use cases of isolated technology. These examples, though rich in information, only partly represent the diverse and broad set or bundle of I4.0 technologies and the causes and effects of deploying such technology in practice at a factory or throughout the firm (Frank, Dalenogare and Ayala, 2019; Büchi, Cugno and Castagnoli, 2020; Cugno et al, 2022). The review also found scant evidence about the trade-off needed for I4.0 adoption. No studies differentiate between I4.0 projects in the form of cross-functional integration within the boundaries of the factory, which improves efficiency, and external integration, which improves responsiveness (Williams et al, 2013; Shukor et al, 2020).

In this vein, the integration of various I4.0 technologies within functions and their effects on the workforce needs further investigation. The review only found rare cases, such as Oncioiu et al, (2019), relating cybersecurity and BDA to improved external integration, while integration with machine learning (ML) is associated with internal integration, production planning and optimisation (Ellefsen et al, 2019; Rauch, Dallasega and Unterhofer, 2019) (section 2.4.3). Similarly, studies rarely found I4.0 technology for cross-functional integration. For instance, the integration of BDA and IIoT was found to enable cross functional alignment (Sader Husti and Daroczi, 2019). Group and individual level studies also require empirical backing to support the existing studies (i.e, Grenčikova, Kordoš and Sokol, 2019; Sanghavi, Parikh and Raj, 2019; Robert, Giuliani and Gurau, 2022). The wider literature calls for stronger research on organisational culture (Song, Kim and Kolb, 2009; Naor, Linderman and Schroeder, 2010) and other social factors, such as employee loyalty and satisfaction (Yee, Guo and Yeung, 2015), as major determining factors, setting the level of support for I4.0 implementation efforts.

The review found growing yet still maturing literature on I4.0 performance. For example, at the smart factory level the review found almost no studies at the factory unit of analysis. Nonetheless, many key performance outcome of I4.0 investigating competitive advantage is still unexplored (Ghobakhloo and Fathi, 2019). Such studies could shed light on how I4.0 technology use at the factory impacts the factory's performance, which could impact the competitiveness of that factory. Instead, the current empirical literature on I4.0 mostly studies performance measures relevant to manufacturing firms (Pfeiffer, Lee and Held, 2019). Interestingly, time-based performance, such as production schedule attainment (Bozarth et al, 2009), is regularly measured in the wider literature on factory performance but is largely ignored in the I4.0 literature. There is also a notable lack of studies measuring sub-unit (e.g., factory) performance based on cultural factors such as I4.0 impact on learning from failure (Spicer and Sadler-Smith 2006; Carmeli, 2007). Future studies could examine other performance indicators relevant to the factory unit of analysis, currently missing in the literature, most notably, conformance quality (Devaraj, Hollingworth and Schroeder, 2004), capacity utilisation (Baumers et al, 2016), delivery quality (Ahmad and Schroeder, 2009), customisation responsiveness (Das and Narasimhan, 2001), and rate of environmental emissions (Zhu and Sarkis, 2004)

### *2.5.3 Gap 3: Vague Enablers and Preconditions*

The I4.0 literature primarily explores organisational enablers and performance outcomes, sidelining other crucial aspects such as data integration, socio-technical considerations, and general capabilities at such levels as the factory, where I4.0 technology is mostly deployed (Meredith, 1987; Banker et al, 2006; Bardhan, Whitaker and Mithas, 2006). For instance, at the smart factory level the review rarely found key enablers such as lean production to be studied (Tortorella and Fettermann, 2017; Sjodin et al, 2018; Tortorella et al, 2019), in contrast to key technologies and enablers such as cyber security, evermore critical for factories with automated operations, which are only discussed at the firm level (Yu and Schweisfurth, 2020; Calabrese, Levialdi Ghiron and Tiburzi, 2021).

These uncharted territories, especially in supply chain research and product lifecycle management, require empirical scrutiny (Kim, Lee and Lee, 2017). Understanding the contractual aspects between I4.0 users and providers during implementation and long-term relational governance is essential but is unnoticed (Zheng et al, 2021). For instance, studies have rarely explored contractual definability and enforceability (Zhang, Jin and Yang 2020) between I4.0 users and providers (Müller, 2019). The lack of empirical evidence on the importance of trust (Wang, Yeung and Zhang, 2011) and crisis preparedness (Carmeli and Schaubroeck, 2008) among I4.0 innovation partners adds further limits to understanding on this matter.

In the same vein, future research could more comprehensively address the role of information, knowledge, and data flow. For instance, investigating absorptive capacity at various levels such as the factory level can clarify the flow of knowledge in the smart factory (Patel, Terjesen and Li, 2012). For instance, at the data level the review found most of the studies discussing big data analytics and cloud usage in the context of the organisation (Narula et al, 2020). Consequently, many important enablers related to the flow of knowledge and data within and among factories is not well understood. Open innovation is a notable I4.0 enabler identified by the wider literature, found to be critical in gaining knowledge for implementation, yet scarcely referred to in the literature except by Pfeiffer, Lee and Held, (2019) and Himang et al, (2020). In addition, external breadth and depth was not comprehensively investigated as a key enabler to implementation of I4.0 production technology (Lorenz et al, 2020). In the same vein, the level of technology scouting and horizontal and vertical technology collaboration (Wang, Chang and Shen, 2015) is expected to strongly define the level of technology use but is rarely found to be studied at a more granular level with limited practical implications. Addressing such limitations could clarify to what extent external knowledge influences manufacturing adoption policy and procedures at various stages of the I4.0 transformation journey.

The review found long-term relational governance during the adoption of new technology and the transformation period is understudied. Prior implemented change practices in preparation for I4.0 adoption are barely covered in the literature (Sakakibara et al, 1997; McKone, Schroeder and Cua, 2001). The review found lean management (Ghobakhloo and Fathi, 2019) and agility (Bibby and Dehe, 2018) increasingly studied at the firm level. Many other factors, such as agility and leanness internally and within the supply chain, remain vastly underexplored at other levels and lack empirical support (Oliveira-Dias et al, 2022). The literature is lacking evidence on the appropriate level of cooperation between raw material suppliers of the firm (Mishra et al, 2016), and strategic suppliers of I4.0 manufacturing technology (Veile et al, 2020). Conversely, the impact of customer relations and value cocreation is another major area which remains relatively unexplored (Royo-Vela and Velasquez Serrano, 2021), for instance, green supply chain management practices of the buyer and supplier (Zhu and Sarkis 2004; Lee, 2008).

Most importantly, integration capability is deemed critical when technological change is introduced in the firm (Afuah, 2001; Amankwah-Amoah, 2017). Nonetheless, the literature remains silent on the need for these capabilities, with few exceptions (e.g., Gu et al, 2019; Ellefsen et al, 2019; Pessot et al, 2021). The wider literature suggests that integration is key for I4.0 adoption. For instance, integration with marketing (Swink and Song, 2007; Feng, Huang and Avgerinos, 2018), sales (O'Leary-Kelly and Flores, 2002), Human Resources (Santos, 2000), and supply chains (Cagliano, Caniato and Spina, 2006). The systematic literature review also revealed several other understudied internal capabilities that could be explored as enablers to I4.0 implementation. For instance, the level of R&D expenditure is expected to impact the rate of innovation and the implementation rate and pace of advanced technology (Lin et al, 2018; Veile et al, 2019; Zangiacomi et al, 2020).

### *2.5.4 Gap 4: Lack of Theoretical Foundations*

Inclusion of an appropriate theoretical foundation can advance the cycle of theory building and theory testing in this growing domain (Rousseau, 2006; Eisenhardt and Graebner, 2007; Suddaby, 2010; Yaniv, 2011; Fiss, 2020). Theory has long been a critical part of valid and generalisable empirical evidence in management studies (Eisenhardt, 1989; Whetten, 1989). Yet the current literature falls short of using theory consistently, causing partial or ineffectual research designs and limiting the relevance of findings. This limits the understanding of many important causal effects of using I4.0 technologies and concepts.

The I4.0 literature often lacks theoretical grounding as it is a relatively new concept. Incorporating established management theories, such as dynamic capabilities (Teece, 2018; Felsberger et al, 2022) and sociotechnical theory (Cimini et al, 2020; Neumann et al, 2021) as the foundation of research can enhance the understanding of I4.0 implementation and its impact on various organisational facets. More importantly, this gap also exacerbates the limited empirical focus on critical sub-units, such as the factory, focusing on the deployment of I4.0 technology. Also, the diffusion of innovation theory warrants further exploration to clarify the adoption of complex systems, which may include multiple I4.0 technologies used in harmony at a factory or for a supply chain (Himang et al, 2020; Call and Herber, 2022). In the same way, grounded theory can be employed to assess priorities across departments and the functions of organisations operating multiple connected factories, which may require varying degrees of I4.0 implementation (Robert, Giuliani and Gurau, 2020; Chang and Huang, 2022).

## ***2.6 Research Objectives and Questions***

Considering the above limitations, the purpose of this research is to clarify key antecedents and outcomes of I4.0 use at the factory. This sheds light on important yet difficult to measure set integration capabilities (as antecedents) for using a variety of I4.0 technologies used in factory settings. The aim is to test the importance of integration capabilities of factory managers as key enablers to combine and utilise complementary I4.0 assets that are advantageous for factory performance. The study also identifies key operational outcomes for a factory using such diverse sets of I4.0 technologies. For the second part the aim is to reveal if less or more broad use of such advanced production technology benefits the output of the factory. Two main research questions are addressed in this research:

1. Can transformational integration capability of factory managers benefit the capability to implement the breadth of I4.0 technologies at the factory?

2. Does the capability to implement the breadth of I4.0 technologies at the factory lead to improved performance and competitive advantage of the factory?

### *2.7 Chapter Conclusion*

This chapter has explored the I4.0 implementation literature in a systematic manner. Full text mining and clustering of major keywords and phrases provided quantitative support for categorising the literature into eleven research streams across five levels. Qualitative review of each stream brought to light the focus of the literature and shortcomings that need addressing in future research. Lastly, the main gaps have been explored in more detail and, based on the above, the research objectives and questions have been framed.

# Chapter 3. Theoretical Background and Hypothesis Development

## *3.1 Chapter Introduction*

The following chapter elaborates on the theoretical background, based on dynamic capability theory (Teece, Pisano and Shuen, 1997; Teece, 2023). The theoretical model is introduced, and the underlying concepts are explained. Based on the theoretical background and the theory of dynamic capability, seven hypotheses are proposed as part of the model. Lastly, each hypothesis is supported with prior relevant evidence in order to test the link and dependency between higher order and lower order capabilities at the factory and to determine competitive advantage outcomes, in this case measured as factory performance.

## *3.2 Theoretical Background*

The theory of dynamic capability (DC) serves as the foundation for this research. For testing the extend and scope of implemented I4.0 technology at the level of the factory, DC theory uniquely clarifies the complex interplay between endogenous and exogenous resources, capabilities, and routines (Collis, 1994; Collis, Moonen and Vingerhoets, 1997). This is particularly useful for technology implementation, often implemented as a long-term, market-oriented endeavour following planning, design, and installation (Lindberg, 1990). DC as a lens for clarifying technology implementation is further supported as the theory considers rapidly changing market environments (Teece, Pisano and Shuen, 1997; Teece, 2007) and exogenous resources (Lewis et al, 2010), both critical in translating adopted I4.0 technology to competitive advantage.

DC claims that organisational capability is developed from organisational routines and habits over time (Wilden, Devinney and Dowling, 2013), clarifying the interplay between heterogeneous distributed resources and often difficult to measure capabilities (Peteraf, 1993; Peteraf and Barney, 2003). For managers, a broader understanding of current capabilities and transformational (or higher order) capabilities is needed to create new capability, strengthening organisational governance activities and decision-making in dynamic markets (Teece, 2014). Also, from the strategic management perspective, DC characterises innovation as the long-term performance generator, emphasising that both current firms and new/existing competitors can invest in new resources, such as advanced production technology (Teece, 2023). Consequently, stronger DC is not aimed at blocking competitors from adopting more advanced production technology. The aim of DC is to create *"new markets and enhancing competition in both newer and traditional markets"* according to Teece (2022). More importantly, a lack of DC leads to a *"digital transformation gap"*, which can delay the growth of digital platforms or in extreme cases lead to failed attempts at digital transformation (Pundziene et al, 2023).

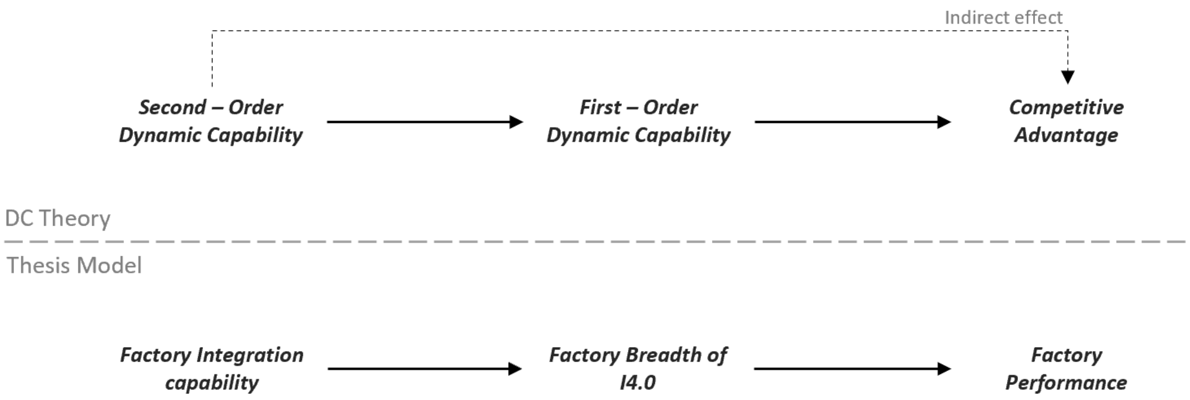
Digital transformation projects often unfold over a period of time as *"departments typically experience different degrees and types of interdependence, and they interact with varying intensities and via different coordination mechanisms"* (Adler, 1995, p.148). Factories adopting advanced production technology benefit from stronger interdepartmental integration capability, to help control and govern interdependencies and coordination mechanisms more efficiently (Twigg, 2002). In effect, DC enhances the ability of factory managers to direct resources and strike a balance between improvement (i.e., efficiency) and innovation priorities (Furlan and Vinelli, 2018).

Dynamic capabilities are divided into (a) first-order dynamic capability to reconfigure resources, routines, and practices. Such resources are widely available or over time become available to the competition in the market in competitive markets (e.g., I4.0 technology and implementation routines). Such commonly accepted traits in a sector are easily imitated by competition or in some cases even standardised within the industry (Teece, Pisano and Shuen, 1997). To fully extract and protect I4.0 value, factory managers can draw on their (b) second-order dynamic capability based on transformational routine changing routines. These routines are not for daily operation of the factory but, as discussed below, explain the learning activities to change existing routines as manufacturing processes become ever more advanced (Ettlie and Pavlou, 2006; Bag, Gupta and Kumar, 2021).

Dynamic capability is strengthened through three sequential steps (Teece, Pisano and Shuen, 1997; Teece, 2014; Teece, 2023). First, sensing or *"identification, development, co-development, and assessment of technological opportunities in relationship to customer needs"*. Second, *"seizing"* or capture of value, by means of mobilising resources identified in the sensing stage. Adopting and using represent easily imitable first-order capabilities. Conversely, higher order (or second order) capabilities act as mechanisms for continued renewal or *"transforming"* of first-order capability to maintain competitiveness in changing markets. Second-order dynamic capability enables new learning routines and practices (Zollo and Winter, 2002). Higher-order DC focuses on change-oriented capabilities (Zahra and

George, 2002) by recombining existing resources, creating new resources and shedding unnecessary or depleted resources (Teece, Pisano and Shuen, 1997). Second-order capability can be more difficult to master as such capabilities are based on path dependent decisions rooted in the factory or organisation's structure and culture (Kyläheiko, Sandström and Virkkunen, 2002; Teece, 2014; Collis and Anand, 2018; Ghosh et al, 2022).

*Figure 2 Thesis conceptual model (Source: Danneels, 2012; Danneels, 2016)*




Digitisation efforts sometimes do not fully consider internal and external resources and practices beyond technology assets (Tabrizi et al, 2019; Björkdahl, 2020). Dynamic capability supports such new manufacturing capabilities by maximising the fit between available resources with the resources available in the market (Schilke, 2014; Liu et al, 2020). As in figure 2, protecting the value of imitable first-order capability is best achieved through the combination of first and factory specific second order DC to create unique and difficult to imitate value by creating routines over time (Griffith and Harvey, 2001; Danneels, 2012; Danneels, 2016; Salvato and Vassolo, 2018). According to Leonardi (2011), routines and technology are often imbricated and interwoven, particularly in production technology acceptance and usage. Overemphasising higher order capabilities related to learning and the transformation of factory assets could lessen the effectiveness of lower-order capabilities of factory managers. On the other hand, overemphasising lower-order capabilities could make the factory prone to imitation and loss of competitiveness. This requires a trade-off between factory efficiency and innovation priorities (Sobrero and Roberts, 2001; Collis and Anand, 2018).

To resolve this issue, the DC theory suggests balancing and timely deploying lower and higher-order dynamic capability as they are intrinsically linked (Easterby-Smith and Prieto, 2008). Organisations with strong ordinary capability that represents accepted industry production routines, such as setting up production machinery with weak higher capability (i.e., learning routines for the same production machinery), may not be able to compete in markets. Digital dynamic capability is defined as "*the ability of a firm, to systematically identify and develop core capabilities for digital transformation"* (Ghosh et al, 2022). Such dynamic capability at the factory strengthens the integration of diverse technology used in production, supported by external and internal resources (Teece, 2020). Developing and strengthening these capabilities at the factory benefits production planning and control (Hasegan, Nudurupati and Childe, 2018) and the balance between improvement and innovation priorities of multi-factory firms (Furlan and Vinelli, 2018).

First-order DC investigating the factory sub-unit acts as adopting and using capability in digital transformation for key I4.0 production and ICT technology, such as adopting and using the industrial internet of things (Ghosh et al, 2022). In the same vein, for smaller manufacturers such digital transformation is also linked to sensing, seizing and transforming resources for competitive advantage (Khurana, Dutta and Ghura, 2022). However, even the more complex management and transformation of resources for larger firms is considered by DC. Therefore, the management and orchestration of technology and its use for factories of any size, age, and production strategy is considered as a first-order dynamic capability in this case (Cetindamar, Phaal and Probert, 2009).

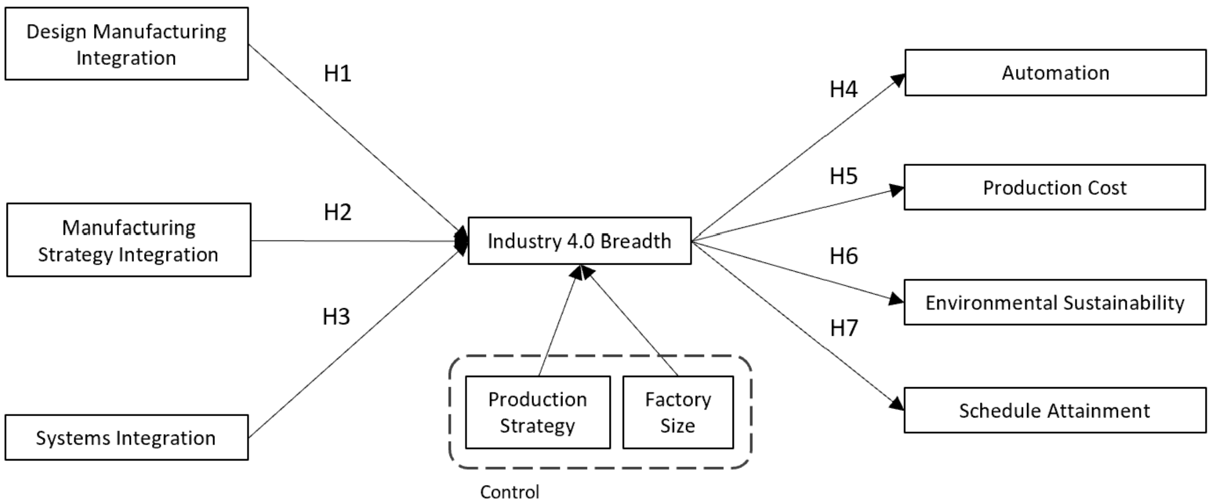
This research argues that merely adopting and using such technological capability at the factory may not provide long-term sustained competitive advantage as competitors may also be able to implement comparable I4.0 technology at a lower cost (Winter, 2003). This will jeopardise any I4.0 investment by a firm or factory as it may not provide the expected results and may even aid the competition in mimicking such capability. The study investigates how to integrate and coordinate technology adoption efforts with internal actors as well as external actors to outline a digital transformation path towards smart factory transformation (Cagliano, Caniato and Spina, 2006; Ettlie and Pavlou, 2006; Zhao et al, 2022).

In multi-unit firms, technology implementation can be facilitated by drawing on information and resources from other functions such as internal functions or different partner factories. This can create unique and hard to imitate value from Industry 4.0 implementation at the factory-level, which other factories could not easily duplicate. In this context, higher-order capability, such as internal integration, lessens internal rivalry among organisational functions during digital transformation (Seran and Bez, 2021), facilitating data sharing. Similarly, collaborating with external actors is associated with increased operational (Wang, Chang and Shen, 2015) and innovation performance (Cheng and Huizingh, 2014). Drawing in knowledge from such external sources and broader collaboration leads to a higher degree of digitisation knowledge and access to technology (Lorenz et al, 2020; El Maalouf and Bahemia, 2023). This can boost the competitive advantage of factories operating in dynamic and constantly changing markets. DC at the factory acts as a competitive priority as it protects the value of investing in costly, risky, and time consuming I4.0 resources.

### *3.3 Research Model*

The model is based on dynamic capability theory. Figure 3 shows the variables and hypotheses of the research model. The model is divided into two stages of testing second order dynamic capability (H1 to H3) as antecedents to first order-capability to orchestrate and operate bundles of I4.0 technology or the breadth of I4.0 technologies.

*Figure 3 Research model*




The second part of the model investigates potential competitive advantage gains and if factory management capability to implement the breadth of I4.0 technologies is positively related to several factory performance outcomes representative of factory competitive advantage, specifically, the factory level of automation, production cost, environmental sustainability in the form of factory emission rates, and schedule attainment of the factory (H4 to H7).

Integration capability is key to using technology at the factory as it was found to be *"the ability to easily expand an operation to incorporate a wider range of products or process technologies"* according to early studies (Swink and Hegarty, 1998). Recent case studies emphasise how I4.0 implementation without prior internal alignment and integration often fail to realise the expected performance outcome (Alcacer et al, 2022; Fedosovsky et al, 2022). In this case, integration at the factory level was measured by quantifying the level of design-manufacturing integration, manufacturing-strategy integration, and systems integration. Integration capability for using I4.0 technology at the factory shows the characteristics of higher-order dynamic capabilities found essential for digital platforms, such as *"sensing the internal environment, value-capturing through connectedness, orchestrating silos, and transforming organisational boundaries"* (Pundziene et al, 2022). Alignment and integration alleviate the technology adoption tensions related to *"variations in a firm's organisational setup"*, such as structural changes across various functions and departments (Matt, Hess and Benlian, 2015). Such higher-order integration capability is also expected to lessen technology adoption tensions at the factory and improve the capability of factory managers to better orchestrate I4.0 technologies previously used in silos. This important relationship is also expected to be important to alleviate factory technology adoption issues based on the setup of the factory.

Higher-order capabilities, such as Integration capability, were found by the review to be highly important but rarely studied at the factory unit-of-analysis (see chapter 2.5). Most notably, the value of integration capability for I4.0 implementation was shown in the fourth stream *"I4.0 Technology and Factory Enablers"* and the eleventh stream *"Horizontal integration"* of the systematic literature review in the previous chapter. Three integration capabilities are proposed as particularly important as antecedents of the factory capability to implement the breadth of I4.0 technologies: design manufacturing integration (Swink and Nair, 2007), manufacturing strategy integration (Narasimhan, Swink and Kim, 2006), and systems integration (Barua et al, 2004).

At the factory level, such higher-order capabilities relate to the transformation of existing resources greatly differing from firm-level dynamic capabilities. This model specifically is related to practices and routines of factory managers related to working with other functions and systems. Therefore, higher-order capabilities related to integrating the various internal systems and departments as well as systems of external suppliers and customers that are partnering with the focal factory are focused on. Theoretically this is justified by DC for technology deployment is supported by internal and external resources (Teece, 2020). DC studies show this is also true for internal and external resources at the factory sub-unit (Banker et al, 2006; Peng et al, 2013). Also, within the organisation in which the factory operates we measure if integration of manufacturing strategy with business strategy develops the capability to implement the breadth of I4.0 technologies at the factory. Lastly, as production is strongly associated with the product manufactured at the factory, the design-manufacturing integration is measured. These higher-order capabilities, instead of focusing on firm practices (i.e., sales and marketing), specifically examine the higher-order dynamic capabilities relevant to top factory managers using broad types of I4.0 technology.

For the second part of the model, the impact of the breadth of I4.0 is linked to five factory operational performance measures to determine the competitive advantage outcome of I4.0 implementation. These factory performances measure the level of automation, production cost, environmental sustainability, and schedule attainment. Regarding performance, the literature review found I4.0 was linked to improved labour productivity (Agostini and Filippini, 2019), production flexibility (Büchi, Cugno and Castagnoli, 2020) and product customisation and quality (Dalenogare et al, 2018). Yet many important factory operational performance measures related to competitive advantage remain unexplored (Xiaosong Peng, Schroeder and Shah, 2011). These include the level of automation (Ritzman and Safizadeh, 1999), production cost, which is more internally dependent (Ragatz et al, 2002), production schedule attainment (Bozarth et al, 2009), and lastly environmental sustainability performance as a result of adopting and using the breadth of I4.0 technology.

As different types and sizes of factories perform differently (Devaraj, Hollingworth and Schroeder, 2004), in this research factory size and production strategy control the breadth of I4.0 technologies. Factory size impacts the level of technology in factories (Marsh and Mannari, 1981). In fact, both process implementation (Netland et al, 2015; Lorenz et al, 2020) and technology implementation (Lorenz et al, 2020) are dependent on the size of the organisation. Second, we control for production strategy. The order penetration point (Olhager and Selldin, 2004; Lorenz et al, 2020) defines factory production strategy as make-to-stock (MTS), make-to-order (MTO), assemble-to-order (ATO) or engineer-to-order (ETO).

Different production strategies in turn best utilise certain manufacturing technologies and present unique challenges and opportunities. Ultimately, production strategy defines production planning and control (Shao and Dong, 2012; Adrodegari et al, 2015) and digital technology implementation at the factory (Aslan, Stevenson and Hendry, 2015; Lorenz et al, 2020).

### *3.4 Conceptual Development*

Below, the main components of dynamic capability are explained. This is followed by a discussion of the causal relationship between the three antecedents and the breadth of I4.0 and the relationship between the breadth of I4.0 and factory performance outcomes.

#### *3.4.1 Theoretical definition*

First-order dynamic capabilities reconfigure the organisational resource base and are distinguished as *"capabilities that allow the firm's fundamental capabilities and resources to change"* (Teece, Pisano and Shuen, 1997; Eisenhardt and Martin, 2000; Zollo and Winter, 2002; Schilke, 2014). Ordinary and first order (efficiency oriented) capabilities are referred to as lower capabilities, while second order (continuous and renewal-oriented) capabilities refer to higher-order capabilities (Collis and Anand, 2018). First-order dynamic capabilities rely on experience and knowledge in *"enabling the reconfiguration of resources and routines"* (Easterby-Smith and Prieto, 2008), in response to organisational and environmental changes (Zahra, Sapienza and Davidsson, 2006). First order capability is characterised as the capacity to carry out new product development (Peteraf and Tsoukas, 2017; Winter, 2003), agility (Shin et al, 2015) and product-process innovation (Anning-Dorson, 2018), absorptive capacity and a collective mind (Ettlie and Pavlou, 2006). Also, dynamic capability is measured as the level of technological sophistication for resource access and development (Stadler, Helfat and Verona, 2013; Danneels, 2016). Investment in first-order dynamic capabilities may not be worthwhile, however, if more flexible competitors can replicate or build similar capabilities at a lower cost (Winter, 2003).

Second-order dynamic capabilities are defined as *"learning to learn"* (Schilke, 2014), or simply "*learning*" capabilities (Easterby-Smith and Prieto, 2008). For manufacturing factories, second-order dynamic capabilities are bundles of interconnected *"routine changing routines"* to reconfigure the vast web of resources (Schroeder, Bates and Junttila, 2002). In this sense, higher-order capability is responsible for *"creating"* or *"adding"* aspects of dynamic capabilities (Danneels, 2002; Danneels, 2008; Danneels, 2012). Schilke (2014) describes second-order capabilities as antecedents of first order dynamic capability. Yet in some cases, such as Schilke (2014) and Wang and Ahmed (2007), first order capabilities can be antecedents of second-order capabilities. For instance, regarding the joint effect on performance, first and second-order dynamic capability can be substituted for each other (Schilke, 2014). Meta routines, originally proposed by Adler (Adler, 1995, Adler, Goldoftas and Levine, 1999), can be improvement or innovation oriented (Furlan and Vinelli, 2018) or meta routines building on absorptive capacity (Mariano and Al-Arrayed, 2018). Such a level of ambidexterity can be achieved through meta routines, such as cross functional product development (O'Reilly and Tushman, 2004; Peng, Heim and Mallick, 2014; Peng et al, 2022).

Second-order dynamic capabilities can also refer to behavioural patterns of top-decision makers, who most often direct second-order change (Peteraf and Tsoukas, 2017). In the case of product development, for instance, second-order dynamic capability refers to *"the capacity for changing the way product development occurs and/or its aims, noticing new productive opportunities"* (Peteraf and Tsoukas, 2017, p.177). Other capabilities are also considered as second order. For instance, customer involvement capability is considered a second-order dynamic capability (Schilke, 2014; Anning-Dorson, 2018). Limitations of first and second-order dynamic capabilities remain, such as the vague understanding of the trade-off between different types of DC and the ability to execute lower-level capabilities (Collis and Anand, 2018).

### *3.4.2 Definition of integration capability*

Integration and alignment between strategies, domain, functions, and infrastructure are widely studied at the organisation level. The findings complement the fragmented and loose studies of the integration capability of factories. Studies identify integration across three levels: internal integration (infrastructure based), external integration (strategy based), and cross-domain integration, spanning across strategies and infrastructures (Gerow et al, 2014). Internal integration is exemplified as the alignment between the organisation and IT processes and infrastructures, defined as *"the link between organisational infrastructure and processes and I/S infrastructure and processes"* (Henderson and Venkatraman 1999, p. 476). External integration reflects the strategic or intellectual alignment of organisation and IT strategies

(Reich, and Benbasat, 1996; Reich and Benbasat, 2000; Chan and Reich 2007). Such information-driven external integration is defined as "*the degree to which the mission, objectives, and plans contained in the business strategy are shared and supported by the IS strategy"* (Chan, Sabherwal and Thatcher, 2006; Gerow et al, 2014). Lastly, cross-domain integration (cross-domain alignment) is defined as *"the degree of fit and integration among business strategy, IT strategy, business infrastructure, and IT infrastructure"* (Chan and Reich 2007, p. 300).

Internal compared to external integration can, in some cases, be more correlated to achieving the desired goals (Zhao et al, 2011; Vargas, Cardenas and Matarranz, 2000) due to a higher level of control over the integration process. It is also relatively more studied at the factory level. For instance, to implement ERP at the factory, interdependence between manufacturing and the marketing function is deemed necessary (Gattiker, 2007). However, the impact of such external communication on the outcome of technology adoption is in large part based on inter-organisational collaboration and therefore indirectly dependent on internal collaboration (Sanders, 2007; Horn, Scheffler and Schiele, 2014). In this context, lateral relations and vertical information systems augment the factory's internal integration capability to extend the external integration boundaries (Williams et al, 2013; Swink and Schoenherr 2014).

To differentiate between them, cross-functional integration within the boundaries of the factory reduces process inefficiencies, while external integration improves responsiveness within the value chain (Williams et al, 2013; Shukor et al, 2020). Both internal and external integration practices are linked to organisational improvements in quality and flexibility (Droge, Jayaram and Vickery, 2004; Koufteros, Vonderembse and Jayaram, 2005; Jayaram and Xu, 2013). Integration and alignment among functions and departments is considered to be an important tool for improving organisational performance (Pagell, 2004; Swink, Narasimhan and Kim, 2006). Also, integration is linked to the volume of operations and the work structure of the subunits in a factory (Blau, 1972; Ettlie and Reza, 1992; Johansson and Olhager, 2004).

Integration benefits advanced technology yet requires constant evaluation of implementation practices and routines to realise the full benefits and improve competitiveness in the market (Riis, 1992). In essence, it is assumed that such inter-functional and inter-system integration capabilities of factory managers can build routines that equally support management of the breadth of I4.0 technology at the factory. This is in line with the results of previous studies on internal integration, finding integration to moderate the use of advanced manufacturing technology (Moyano-Fuentes, Sacristán-Díaz and Garrido-Vega, 2016). In some cases, cross-departmental integration is vital for implementing radical technology (Afuah, 2001). Even within single departments of a factory, such as production machines from various lines, integration improves task coordination and waste minimisation (Lenz, Wuest and Westkamper, 2018).

### *3.4.3 Definition of breadth of factory I4.0*

The breadth of I4.0 at the factory measures the number of different types of I4.0 technology adopted and used for factory operation. It is increasingly critical to measure the breadth of I4.0 due to the ever-growing commercialisation of different types of I4.0 ICT and production technology. The breadth of I4.0 at the factory can also be compared to similar concepts. For instance, *"technological breadth"* or technological diversification, which is greater than product diversification (Breschi, Lissoni and Malerba, 2003). However, whereas technological breadth measures the *"diversity of the technological knowledge of a buyer's supplier network"* (Gao, Xie and Zhou, 2015; Palit, Hora and Ghosh, 2022), the breadth of I4.0 measures the diversity of production technology used in daily operations (Büchi, Cugno and Castagnoli, 2020; Bettiol et al, 2023).

The capability of top factory managers to control the breadth of I4.0 is also desired to achieve greater complementarity among the technology resources of the factory. This can greatly benefit complementary technologies, such as robotics, simulation technology, and I4.0 ICT technology, such as IoT and big data analytics. Similar technology centric functions (besides manufacturing), such as R&D, benefit from diversified technology platforms as this partially dampens the negative effects of rapid changes in the market (Helfat, 1997; Parmigiani and Mitchell, 2009; Miozzo, DiVito and Desyllas, 2016). Such complementarity between assets and the capability to manage technology sets is also critical for the success of high-technology mergers and acquisitions (Makri, Hitt and Lane, 2010).

Prior empirical research often investigated I4.0 technologies in a focused but also isolated manner (e.g., Benzidia, Makaoui and Bentahar, 2021; Benzidia, Makaoui and Subramanian, 2021) and did not necessarily consider the synergies and complexities characteristic of managing and orchestrating several I4.0 assets in harmony (Büchi, Cugno and Castagnoli, 2020; Cugno, Castagnoli and Büchi, 2021). Given that having the technological capacity does not imply its operational use (Danneels, 2016), key I4.0 technologies act as *"platforms for organisational capabilities of companies"* (Zangiacomi et al, 2020). Such transformational technologies require changes to organisational practices and structure (Leonardi and Bailey, 2008), similar to the way in which IT adoption progressed over time (Gregory et al, 2018). In this sense, the "complementarity effect" based on how, for instance, ERP and e-business technology resources are implemented to more broadly contribute to business value than the effect of ERP or e-business technology alone (Hsu, 2013). Information technology is a critical platform. The smart factory is based on layered complementary platforms to enable more advanced capabilities, such as cyber physical systems (Benitez, Ghezzi and Frank, 2023).

#### *3.4.4 Definition of factory performance and competitive advantage*

In the strategic management literature competitive advantage is mostly reflected by financial and business performance, while the production and operations management literature to some degree examines operational performance at the factory (Csiki, Demeter and Losonci, 2023). Studies on the effect of the breadth of I4.0 on performance have only so far considered the firm and product level. At the firm level, competitive advantage is mostly examined as flexibility, quality, delivery and cost while other measures of competitive advantage related to production such as schedule attainment and production cost are missing from the literature. The breadth of I4.0, for instance, is linked to improved production flexibility, speed of prototyping, output capacity, setup cost, machine downtime, product quality, customer satisfaction (Büchi, Cugno and Castagnoli, 2020). Equally, greater breadth of I4.0 improves human resource productivity (Cugno, Castagnoli and Büchi, 2021), recovery from the recent Covid-19 pandemic (Cugno et al, 2022), and advances green manufacturing (Chang, Zhang and Liu, 2022). Other studies found no significant relationship between the breadth of I4.0 and business to business firm performance, while noting the positive and significant moderating effect of the breadth of I4.0 on the relationship between the servitisation strategy and business to business performance (Bortoluzzi et al, 2022).

At the factory-level, the manufacturing strategy (Miller and Roth, 1994; Brown, Squire and Blackmon, 2007) directly impacts manufacturing performance based on available resources (Schroeder, Bates and Junttila, 2002). In the context of the smart factory, these resources can be both the technology implemented (Klassen and Whybark, 1999) as well as the change practices implemented (Sakakibara et al, 1997; McKone, Schroeder and Cua, 2001). There are several performance measures defining the state of production and value created by the factory, revealing the short-term success and lasting manufacturing capabilities (Ferdows and Meyer, 1990; Leachman, Pegels and Shin, 2005).

The above studies reinforce the importance of the breadth of I4.0 for competitive advantage. The literature on DC provides a more complete view of how important I4.0 technology adoption is in leading to competitive advantage. For instance, IoT and CPS, as well as other critical I4.0 technology, enable competitive advantage for manufacturing SMEs (Masood and Sonntag, 2020; Estensoro et al, 2022). The literature on DC also exemplifies manufacturers combining different types of capabilities to gain competitive advantage through I4.0 (Ding, Ferras Hernandez and Agell Jane, 2023). In this context, the combinatorial effect of these capabilities' competitive advantage gains are not easily countered by competitors.

### *3.4.5 Interaction among capabilities*

The above lower-order (breadth of I4.0) and higher-order (Integration) capabilities act as a knowledge-transfer tool to strengthen the capability to restructure, reorganise and reposition the production assets used for manufacturing to gain competitive advantage. In this case, integration routines and practices represent a higher order capability, improving the lower-order capability of adopting and using a range of different I4.0 production technologies. Digital firms with such highly scalable resource bundles experience *"significant opportunity costs of integration"* compared to outsourcing, which also drives "*hyper specialisation"* and *"hyper scaling"* as an indirect outcome (Giustiziero et al, 2023).

The capability to implement the breadth of I4.0 technologies is considered a powerful tool for expanding and reconfiguring existing resources, yet often in combination with other transformation oriented second order capabilities (Danneels, 2008; Danneels, 2016). This sets the competitive advantage gains of DC approach to I4.0 apart from other static or reactionary competitive strategies. This is because the continuous cycle of sensing, seizing, and changing routines and practices accordingly is not only to maximise competitive gains but also to provide sustained competitive advantage in emerging markets (Felsberger et al, 2022; Ed-Dafali et al, 2023). Similarly, the breadth of I4.0 can be considered as a factory asset management capability and the three second-order integration capabilities as tools for asset complementarity in the pursuit of competitive advantage (Helfat and Campo-Rembado, 2016). The latter has been identified as *"capabilities that an enterprise must possess in order* *to obtain the economic benefits of an innovation, technology, or strategy*" (Christmann, 2000). The integration capability of factory managers supports the use of available I4.0 technology platforms in the market, such as "*Networked Manufacturing Operations platforms; Vertical Integration platforms; End-to-End Engineering platforms; Horizontal Integration platforms"* (Benitez, Ghezzi and Frank, 2023). Ultimately, as the I4.0 technology is imitable, the factory specific integration capability among the technology resources creates competitive advantage (Hsu, 2013).

## *3.5 Hypothesis Development*

### *3.5.1 Design Manufacturing Integration (DMI) and Breadth of I4.0*

DMI is defined as the level of alignment and integration between the design function and production function of the manufacturer, focusing on the link between product and production process (Swink and Nair, 2007; Thome and Sousa, 2016). Recent studies have found valuable evidence linking DMI to several different types of I4.0 technologies. This strongly suggest a positive link between DMI capability and the capability to implement the breadth of I4.0 technologies at the factory.

Studies have found DMI to depend in large part on incorporating and harmonising department specific resources to overcome barriers between the two functions (Vandevelde and Van Dierdonck, 2003). In light of this, studies associate DMI capabilities with increasing use of advanced manufacturing technology. It is argued that strong DMI within firms indicates a similar effect at the sub-unit (factory) level, leading factories to better manage their breadth of I4.0 technology. For instance, the integration of existing design technology and more advanced manufacturing technology across the two functions benefits from the development of DMI capability. Several technologies have been exemplified in the literature supporting this claim. For instance, computer aided design (CAD) and computer aided manufacturing (CAM) substitute for the sequential design process by harmonising and coordinating efforts between functions (Ettlie and Reifeis, 1987). Similarly, factory robotics and flexible manufacturing system (FMS) are linked to hierarchical integration and vertical coordination systems as centralised control remains necessary (Ettlie and Reza 1992).

It is expected that cross-departmental technology integration beyond CAD/CAM integration is required to more broadly implement the available I4.0 resources (Droge, Jayaram and

Vickery, 2004; Guo and Zhang, 2010; Kumar, Madan and Gupta, 2013). In this context, the use of IoT for increasing collaboration among divisions and departments beyond production is recommended (Fukuzawa et al, 2022). Similarly, industrial IoT (IIoT) is used for the integration of data from design tools and production machines (Thramboulidis and Christoulakis, 2016; Sousa, Mendonca and Machado, 2022). Furthermore, the use of cloud-based storage and computing increases if integration of the design and manufacturing is strengthened (Park, Woo and Choi, 2020; Shahin et al, 2020). Similarly, additive manufacturing could be more effectively implemented if DMI capability is adequate (Ranjan, Samanth and Anand, 2017). DMI broadens the use of artificial intelligence to augment design and additive manufacturing for allocating tasks efficiently (Elhoone et al, 2020).

Other I4.0 examples found that the integration of virtual reality (VR) technologies was primarily used in design and additive manufacturing to benefit product innovation as design ideas can be more easily and rapidly prototyped and manufactured (Zawadzki and Zywicki, 2016). In this context, an integrated simulation environment can harmonise the different standards across the design and production departments (Ugarte et al, 2022). Integration is ideally controlled, with the intensity ranging from simple coordination to segmented coordination for the first production batches and virtual coordination using advanced 3D modelling and simulation (Abecassis-Moedas and Moatti, 2022). In the context of I4.0, such integration occurs between physical elements, virtual models, and the services of the smart factory (Fatorachian and Kazemi, 2018; Cheng et al, 2018). Specifically, DMI improves tolerance control and process monitoring capability (Yu and Shen, 2009). Such technological integration also benefits the security of the smart factory (Tuptuk and Hailes, 2018) as more data from a wider range of functions and systems is made available to I4.0 users.

Thome and Sousa (2016) characterise DMI as a mechanism to maintain cross-functional coordination and ultimately production flexibility during technology implementation. In fact, manufacturers strong in DMI implementing volatile production technology (i.e., easily imitable by the competition) obtain greater competitive advantage. In other words, the more complex and customised the product the higher the breadth of I4.0 needs to be to produce such increasingly complex products in the smart factory (Devaraj, Hollingworth and Schroeder, 2004; Vickery et al, 2016, Kim, 2022; Turco and Maggioni, 2022). If integration capability is not adequate for highly complex products and production systems this will induce cognitive and relational complexity amid the firm's functions (Wang and Tunzelmann, 2000). Functional managers working with I4.0 technology also benefit from DMI due to the increasing comprehension of manufacturability at the design stage, which is deemed critical for complex production to improve design quality (Swink and Calantone, 2004). Such integration between design and manufacturing is strongly linked to design for manufacturability (Chang and Tang, 2001).

In light of the above, it is expected that DMI is necessary for factories using complex production setups, comprising multiple I4.0 technologies. Such integration between the design and the manufacturing function improves product-process innovation, enhancing manufacturing productivity and capacity (Ettlie and Reza, 1992; Ettlie, 1995). More importantly, DMI determines the use of new manufacturing systems and is significant in the configuration and planning of production (Bozarth, and McDermott, 1998). It is therefore logical to assume that complex sets of factory I4.0 technologies require DMI capability to support effective and efficient operation. A tighter fit between design and manufacturing is also desired for cost reduction (Delbressine and Wolf 1990; Ettlie, 1995). Equally, a technological fit between design and production is found to reduce lead times (Liker, Collins and Hull, 1999; Droge, Jayaram and Vickery, 2004; Jayaram and Xu, 2013). Consequently, inadequate integration may result in diminishing functional specialisation (Rusinko, 1999). Specifically, a lack of DMI could lead to weak design specialisation (Swink and Song, 2007) and ultimately raise issues and disruptions during I4.0 adoption (Abecassis-Moedas and Moatti, 2022). Other studies also find that a lack of integration negatively impacts volume flexibility, lead times and the quality of the product (Turkulainen and Ketokivi, 2012). There are reasons to believe that low production quality, flexibility, and yield due to a lack of fit between design and manufacturing technology is expected to diminish the ability to control the breadth of factory I4.0 technology.

The wider literature found that competitive advantage and technology implementation also depend on cultural and structural collaboration between design and manufacturing. For instance, stakeholder integration is deemed critical between the design and manufacturing departments to improve the production planning strategy (Flatscher and Reil, 2016). Also, technology is more easily planned for and deployed if cross-functional conflict is mitigated by transparent information exchange, such as using IoT to connect stakeholders (Chen et al, 2021).

Swink and Nair (2007) measure DMI at the factory-level and argue that DMI is a *"complementary asset"* to advanced manufacturing technology such as ERP, MRP, CAD, CAM, and robotics. Yet the connection of DMI to the breadth of I4.0 technology in unknown. Such higher order capability informs factory managers of the performance of new technology and partially compensates for the increasing availability of sometimes volatile I4.0 technology to factories competing in the same sector. Other factory level studies reinforce the use of data integration tools, such as order management systems (OMS), in enabling data collaboration among product development teams and product development and manufacturing processes (Banker et al, 2006). Particularly for SMEs, the internal alignment and integration of departments is deemed critical in technology implementation despite them having a simpler organisational structure compared to larger firms (Santos et al, 2020; Mason, Ayre and Burns, 2022).

In summary, comprehensive integration between the design function and the manufacturing faction, less so for routines such as job rotation (Thome and Sousa, 2016), can impact the breadth of factory I4.0 technology deployment and use. These integrative capabilities boost competitive advantage and the technology orchestration of various departments (Koufteros, Vonderembse and Doll, 2001; Swink and Nair, 2007) by drawing on technological, structural, and cultural alignment among the various elements of the two functions. It is therefore hypothesised that:

H1: The design-manufacturing integration capability of factory managers is positively related to adopting and using the breadth of I4.0 technologies at the factory.

### *3.5.2 Manufacturing Strategy Integration (MSI) and Breadth of I4.0*

Strategy integration at the factory is defined as *"the extent to which a manufacturing plant makes use of interactions with other intra-organizational [strategy] units to make its program objectives and practices consistent with its internal and external requirements"* (Swink, Narasimhan and Kim, 2005). Cross-departmental coordination aligns business strategy with manufacturing strategy (Schroeder, Anderson and Cleveland, 1986). In the traditional literature, MSI has been linked to benefits such as improving environmental performance (MacCormack, Newmann III and Rosenfield, 1994; Rocky Newmann and Hanna, 1996), cost efficiency and process flexibility (Swink, Narasimhan and Kim, 2005), and to improving factory leanness and agility (Narasimhan, Swink and Kim, 2006). The literature suggests that MSI supports the breadth of I4.0 technology. For instance, studies link manufacturing-strategy integration (MSI) to technology management in dynamic markets (Arana-Solares, Ortega-Jiménez and Alfalla-Luque, 2019). Manufacturing-strategy integration (MSI), like the characteristics of DMI, enhance and enable greater levels of communication through digital channels, improving vertical integration (Swink, Narasimhan and Kim, 2005). Recent studies paint a more comprehensive picture of MSI being positively related to the breadth of I4.0 technologies used in factories.

Such integration of information technology is used to gain competitive advantage (McKeown and Philip, 2003). For instance, integration between enterprise resource planning (ERP), often used in corporate strategy, and manufacturing execution systems (MES) that run production, supports the firm's operations (Tonelli et al, 2016). Such MSI leads to greater cross-functional understanding of commercialising technology (Zahra and Nielsen, 2002). Early studies of MSI also found that such integration assists firms in balancing between product differentiation and delivery performance (Swamidas, El-Tahan and Arockiasamy, 1986). In this context, an integrated manufacturing strategy improves product quality, delivery, flexibility, and cost (Joshi, Kathuria and Porth, 2003; Amoako-Gyampah and Acquaah, 2008).

Logically, if internal strategy is disconnected from production, installation is delayed or in some cases could fail due to unforeseen circumstances during adoption. For instance, if work organisation plans are shorter than technology implementation plans and there is a lack of integration then installation may become more burdensome (Lindberg, Voss and Blackmon, 1988). Small and medium sized factories receive additional benefits from such cross-functional integration as increased ambidexterity empowers managers to exploit limited resources more efficiently (Sahi, Gupta and Cheng, 2020). MSI is expected to support the factory's capability to implement a wider range of production technologies as uncertainties related to technology planning and implementation are reduced (Lindberg, 1992). In this context, it is expected that the breadth of I4.0 technology at the factory is more efficiently managed and orchestrated if supported by adequate levels of MSI.

Complementary to the above, recent studies more strongly suggest that technology alone may not deliver the desired performance in aligning manufacturing and strategy (Domínguez Machuca et al, 2011). In fact, the factory of the future is enabled by a combination of manufacturing strategy, rate of innovation, and technology adoption (Pessot et al, 2021). MSI requires cultural and data integration between production and strategy departments. Such centralisation of corporate planning and manufacturing delivers significant business value (Telukdarie et al, 2018). This value is explained by factory case studies claiming that competitive priorities vary for different business functions (Macchi, Savino and Roda, 2020). In this context, studies have found top management support to be critical in integrating business and manufacturing strategy, regarded as advantageous in setting standards and in synergising documentation (Zeng, Shi and Lou, 2007).

The cultural and data elements of MSI, if noted by management, can be leveraged to amplify the communication of the manufacturing strategy to the factory, empowering personnel in decision-making (Machuca et al, 2011). It should be noted, however, that such communication channels are not one way, as the strategy function also greatly benefits from production data infrastructure to outline competitive strategy. In this context, factory personnel can access and share information more easily (Schoenherr and Swink, 2012), improving the monitoring, control, and scheduling of tasks at the factory (Murugaiyan and Ramasamy, 2021). This solidifies support for a higher-order integration capability, such as MSI, as a key antecedent to using more advanced manufacturing technology.

The hypothesis suggests that a lack of MSI hinders the adoption and use of the breadth of I4.0 technology. More importantly, not all business functions are equally involved in the digital transformation process (Zheng et al, 2021). This may lead to a different breadth of I4.0 technology used within different functions at the factory due to a lack of MSI and disconnected strategies. Understanding the digital maturity of individual functions and departments, particularly strategy and manufacturing, enables process innovation (Chirumalla, 2021). Specifically, the integration of informational systems (vital for corporate planning and manufacturing production management) is found to expand I4.0 use (Alcacer et al, 2022). It is therefore hypothesised that:

H2: The manufacturing-strategy integration capability of factory managers is positively related to adopting and using the breadth of I4.0 technologies at the factory.

### *3.5.3 Systems Integration (SI) and Breadth of I4.0*

Systems integration is defined as the unification of information systems and databases to enhance the process of, and support for, the flow of administrative and management decision-making (MacLaghant 1998; Markus, Petrie and Axline, 2000; Mendoza et al, 2006). In practice, the uneven adoption of technology across the business leads to various information systems being used in isolation. Such segregation, in parallel with disconnected systems across the supply chain, hinders technology deployment and the creation of digital value (Dong, Xu and Zhu, 2009; Zangiacomi et al, 2020). In light of this, systems are often integrated, particularly if new technology is adopted, to smooth the flow of information and improve information transparency for administrative support, as well as for harmonised factory/business management decision making (Mendoza et al, 2006).

Previous studies have shown some evidence on this matter. For instance, the *"cross-domain alignment"* of data moderates the link between business and IT strategy and reinforces business infrastructure and IT infrastructure (Gerow, Thatcher and Grover, 2015). Grouped into four progressive levels of point-to-point integration, structural integration, process integration, and external integration, continuous systems integration reflects the evolution from basic information exchange to managing information flow between applications, to ultimately achieve external integration with supply chain partners (Schmidt, 2009). Such a proactive IT stance involving selective standardisation and integration to maintain flexibility in adopting new technology is preferred (Agarwal and Sambamurthy 2002; Ross and Weill 2005; Lu and Ramamurthy, 2011). Also, systems integration enables inter-firm and intra-firm partnerships by promoting digital infrastructure for merging and integrating information from various functions (Bharadwaj, 2000). It is increasingly evident that at the factory the capability to integrate internal departmental systems and external systems leads to the development of the capability to implement the breadth of industry 4.0 at the factory, as discussed below.

Internal systems integration capability has been shown to enable technology use at the firm level. It is important to note that integrated business systems only meet about 70% of the needs of a business. This is because the majority of industry 4.0 information technology used for data warehouses, enterprise resource planning (ERP) systems, intranets, and extranets requires different integration processes and a unique approach based on a multitude of standards and frameworks (Markus, Petrie and Axline, 2000). In this sense, systems integration capability acts as a transformational mechanism (attributed to higher-order capability) to harmonise business-units with isolated or partial integration (Goodhue, Wybo and Kirsch, 1992).

Previous studies specifically characterise alignment, synergy, assimilation, and partnership with other internal functions as a systems integration strategy beneficial to technology deployment (Reich and Benbasat, 1996; Chan et al, 1997; Armstrong and Sambamurthy 1999;

Bharadwaj, 2000; Ross, 2002). In this context, data consistency is critical for both enterprise-application integration and business-process integration. This is achieved through a standardised and consistent use of definitions and exchange of information, thus promoting the integration of systems over time (Karimi, Somers and Bhattacherjee, 2009). This is further reinforced by similar studies characterising internal *"IS-business partnership"* capability as a process of integration and alignment between the IS function and other functions of the firm. Other studies promote integration of the entire firm (van der Zee and De Jong, 1999; Wade and Hulland, 2004; Chan and Reich, 2007, p. 300; Porra, Hirschheim and Parks, 2014). At the factory level this relationship is assumed also to hold true due to the need to align and integrate the multitude of factory sub-systems with the wider business systems.

Within the external context, systems integration is known to provide "*explicit coordination"* between buyers and suppliers yet requires investment to maintain systems compatibility as systems evolve (Dedrick, Xu and Zhu, 2009). Systems integration, in contrast to e-procurement, aims to reduce the number of suppliers and focuses on richer information sharing and tighter collaboration between the buyer and supplier (Dedrick, Xu and Zhu, 2009). Substituting expansion of the factory's supplier base with stronger systems integration greatly benefits the adoption of advanced production technology and the breadth of I4.0 as tight and long-term collaboration between a I4.0 provider and I4.0 user is often paramount in the success of the production technology (Frank, Dalenogare and Ayala, 2019; Benitez, Ayala and Frank, 2020; Han and Trimi, 2022; Veile, Schmidt and Voigt, 2022; Benitez et al, 2022). In this sense, supplier integration enhances the factory's efficiency and innovation capability while customer integration often only enhances efficiency capability (Peng et al, 2013).

Further evidence points to the potential positive link between SI and the capability to adopt and use I4.0 technology at the factory alongside traditional legacy production machinery. The capability to align existing information assets, such as IT resources, with newly deployed IT investments is critical in technology adoption (Schweikl and Obermaier, 2020). This is suspected to be true for legacy systems integrated with I4.0 technology and integration among other advanced production assets. Other studies reinforce this link and argue for a standardised, scalable architecture for systems integration across the business. For instance, enterprise application integration (EAI) enables systems integration with existing applications (Mendoza et al, 2006). Similarly, resource planning systems (RPS) support enterprise-wide data integration across multiple functions (Davenport, 1998; Scott and Vessey, 2000). RPS can integrate ERP systems with advanced planning and scheduling (APS) systems, and material requirements planning (MRP II) systems. This could potentially help managers gain access to, and make sense of, factory data on suppliers, customers, production planning, shop floor control, stock control, and data from the order processing stage of manufacturing. The availability of such data is expected to develop the factory manager capability to orchestrate and use multiple synergetic I4.0 technologies at the factory.

Systems integration capability has been found to merge knowledge and make use of inside-out and outside-in resources, improving the use of technology standards (Feeny and Willcocks, 1998; Ross, 2002). Factory managers can leverage such systems to manage product specifications, and match production processes across multiple factories (Schroeder and Flynn 2001). Given the above, it is proposed that systems integration is beneficial for adopting and using the breadth of I4.0 technology at the level of the factory. This is evident from the internal, external and technology elements of systems integration and the benefits for I4.0 technologies such as IT and ERP adoption in the past. It is therefore hypothesised that:

H3: The systems integration capability of factory managers is positively related to adopting and using the breadth of I4.0 technologies at the factory.

#### *3.5.4 Breadth of I4.0 and Level of Automation*

Technology is often deployed to increase the level of process automation. The following hypothesis proposes the factory manager's capability to implement the breadth of factory I4.0 technology to increase the level of automation at the factory. Studies support this view by showing that industry and strategy determine the required level of automation at the factory (Rosenthal, 1984).

In the traditional literature, studies compare the level of automation in product-focused factories with process-focused factories, showing the latter to focus more on discrete manufacturing processes and utilise more flexible processes and machinery with a higher labour overhead (Ritzman and Safizadeh, 1999). In contrast, product-focused factories focus on continuous manufacturing processes with a higher capital intensity and fixed automation, resulting in lower labour overheads yet increased training needs for factory workers. This is further reinforced by previous research on this matter identifying factory automation as one of the major overheads in manufacturing that needs to be carefully planned and executed (Blau et al, 1976; Marsh and Mannari 1981). Other studies suggest that more advanced and interconnected manufacturing technology can mitigate the high costs inherent in automation (Michael and Millen, 1985; Dean et al, 1990; Ittner and Macduffie, 1995; Dotoli et al, 2017). This is because automated machinery is becoming more capable of collecting, storing and transmitting data to other functions (Ittner and Macduffie, 1995).

More recent studies have provided further evidence in support of adopting and using a broad set of I4.0 technologies to improve automation. The advent of I4.0 is set to significantly improve intelligent automation as machines can become more autonomous and self-sustaining, while maintaining human decision-makers in the loop (Jayasekara et al, 2022; Hughes et al, 2022). For instance, resource allocation and scheduling can be further automated, given access to reliable production data and virtualisation of factory processes (Zhang et al, 2021). Automated production control can significantly boost production given a constant stream of reliable production data with minimal packet losses and delay (Dotoli et al, 2017). Others reiterate the need for data extraction as essential for automation solutions (Szalavetz, 2019). Such a level of automation can be achieved through implementation of both I4.0 manufacturing and information and communication technology (Oesterreich and Teuteberg, 2016; Frank, Dalenogare and Ayala, 2019; Vlachos et al, 2021).

Other studies suggested that technology is not a precondition for automation. For instance, digital automation can be implemented with and without the application of sensors (Tortorella, Giglio, and van Dun 2019; Rossini et al, 2022). Some evidence even indicates that highly automated manufacturing and assembly lines are rarely used in practice in favour of mechanically assisted manufacturing and manual assembly respectively (Spena et al, 2016). In this vein, studies suggest that factories with highly automated production and assembly experience lower flexibility (Koste, Malhotra and Sharma, 2004; Yu and Schweisfurth, 2020). The level of automation needed in practice has been debated within the literature, with proponents viewing automation as analogous to establishing and running assembly lines and opponents raising de-skilling issues within the workforce (McMurtrey et al, 2002). In some cases, the level of advanced manufacturing technology (AMT) is measured in terms of the intensity of automation (Chen et al, 2018).

A lack of flexibility and other negative implications of automation are mitigated by using capabilities (e.g., lean, learning) to enable manufacturing technology (Tortorella et al, 2021; Rossini et al, 2022, Tortorella et al, 2023). The literature on this topic suggests the complexity of automation, due to the many variabilities in practice, can be mitigated by developing such complementary *"reasoning capability"* to facilitate automation decision-making in manufacturing (Goh et al, 2020). It would be logical to assume that automation can improve by strengthening other higher order capability, such as integration, to diminish the negative effects of using standalone I4.0 technology. Inadequate automation is associated with errors and reduction in operational and product quality (Salovaara, Lyytinen and Penttinen, 2019). To overcome the shortcomings of both humans and machines in production, the implementation of I4.0 aims for a human-centric approach to automation (Theorin et al, 2017; Bibby and Dehe, 2018; Lin, Wu and Song, 2019; Stentoft et al, 2021). Large companies in particular can leverage their rich resource base to automate operations without major disruptions to the workforce (Gupta and Whitehouse, 2001). This is because larger companies have access to a higher breadth of production technologies or *"a set of technologies that allow [the factory] to perform machine operations and operations within systems, without significant human intervention"* (Papulová, Gažová and Šufliarský, 2022). For instance, such human centric industrial automation can detect faults 70% faster using a 3D digital model, digital shadow and digital twin technologies to inform automation engineers vis-à-vis the state and quality of production (Schamp, Aghezzaf and Cottyn, 2023).

In summary, the literature provides strong evidence on increasing levels of automation if bundles of technology are seized by factory managers. The evidence further shows that bundles of technology enabled by other fundamental capability can automate tasks to a higher degree (Martell et al, 2023). It is argued that this to some degree reduces the avoidance of automation at the factory level. It is therefore hypothesised that:

H4: The capability to implement the breadth of factory I4.0 technology is positively related to the level of factory automation.

### *3.5.5 Breadth of I4.0 and Production Cost*

The initial investment of isolated I4.0 remains high, yet there is mounting evidence supporting improving cost performance for bundles of technology. In some cases, greater breadth of I4.0 technology is related to lower set-up costs (Büchi, Cugno and Castagnoli, 2020). In general, overall equipment effectiveness has a direct effect on minimising production losses and production costs (Gupta and Vardhan, 2016). Production costs can also be reduced by having in place a coherent manufacturing strategy (Ward and Duray, 2000). Most notably, advanced and disruptive manufacturing technology is found to lower factory production costs as costly labour-intensive processes are increasingly automated (Boyer and Lewis, 2002; Choi, Kumar, Yue and Chan, 2021; Bai, Li and Xiao, 2022; Tripathi et al, 2023).

Other studies support the notion of reduced production costs as a major benefit of I4.0 and reconfigurable manufacturing systems (Haddou Benderbal and Benyoucef, 2019; Ralston and Blackhurst, 2020; Milisavljevic-Syed, Li and Xia, 2023). Empirical evidence reinforces this by providing cost benefit mathematical models and a cost optimisation approach for firms adopting I4.0 (Alami and ElMaraghy, 2021; Khettabi, Benyoucef and Boutiche, 2022). Other practices, such as lean manufacturing and agility in digitisation environments, have resulted in lower production costs (Buer et al, 2021; Ding, Ferras Hernandez and Agell Jane, 2023). Conversely, some studies show no significantly positive link between digital maturity and production costs due to a lack of cost focus and delayed performance realisation (Lorenz et al, 2020).

In practice, the production cost is dependent in large part on internal integration across functions (Jayaram and Xu, 2013; Williams et al, 2013) and external integration (Wong, Wong and Boon-itt, 2020). In addition to internal integration, customer, and supplier (external) integration influences production costs positively (Wong, Wong and Boon-itt, 2020). Studies reinforce this yet argue that the use of network technologies alone is not significantly related to cost reduction (Blome, Schoenherr and Kaesser, 2013; Paolucci, Pessot and Ricci, 2021). The use of I4.0 technology in the supply network is particularly significant if products are highly personalised and customised (Katoozian and Zanjani, 2022).

The capability to implement the breadth of I4.0 technologies is expected to be facilitated by internal integration, which empower cross functional teams to coordinate product design and process selection, instrumental in reducing production costs (Gupta and Vardhan, 2016). Several studies have noted the production cost benefits of isolated I4.0 technology, which supports the hypothesis that the capability to implement the breadth of I4.0 reduces factory production costs. For instance, access to real-time data, big data analytics capability and the crowdsourcing of data is known to reduce production costs for digitisation (Blohm, Leimeister and Krcmar, 2013; Shivajee, Singh and Rastogi, 2019). Some studies even suggest that a lack of information technology, such as cloud services, cause high costs (Azadi, Moghaddas, Cheng and Saen, 2021). Likewise, manufacturing analysis systems, automated inspection systems, and robotic assembly and disassembly reduce production costs (Prieto et al, 2002; Shukor and Axinte, 2008; Daneshmand et al, 2023). 3D printing is associated with lower costs as parts can be made only when needed (Baumers et al, 2016; Li, Kucukkoc and Zhang, 2017; Zhang et al, 2020). On the other hand, some studies associate additive manufacturing to higher production costs compared to, for instance, injection moulding (Costabile et al, 2017; Pozzi, Rossi and Secchi, 2023, Top et al, 2023).

Industry 4.0 technology is linked to reduced energy consumption, which accounts for major production expenses in certain process driven industries (Liu and De Giovanni, 2019; Rajput and Singh, 2021). In this context, energy technology supports the reduction of production costs (Chai et al, 2021). Alternative cleaner sources of energy have also been proposed to reduce production costs for digital data centres within the context of I4.0 (Liang et al, 2022). Other studies, on the other hand, find that green technology improves labour productivity but not production costs (Song et al, 2022).

In sum, the above studies reinforce the claim that industry 4.0 technology and, more specifically, bundles of technology, if adopted properly improve production costs. Although some studies suggest otherwise, most evidence supports this claim due to increased automation and access to data depending on the breadth of I4.0. Therefore, it is hypothesised that:

H5: The capability to implement the breadth of factory I4.0 technology is positively related to the factory production costs.

*4.5.6 Breadth of I4.0 and Environmental Sustainability*

There is an extensive literature on clean manufacturing technology, mostly at the organisational level, with increasing studies specifically investigating the impact of I4.0 on factory environmental performance. Firm-level studies have found that advanced manufacturing technologies such as AR, CPS, BDA, AM, IoT, cloud, and autonomous vehicles (AV) reduce the frequency of environmental accidents while preventing and controlling pollution (Yakovleva, Sarkis and Sloan, 2012; Yavuz et al, 2023). Therefore, it is argued that using a broader set of advanced manufacturing technologies at the factory-level also results in a higher factory environmental performance. This is supported by three primary factors leading to the breadth of I4.0 technology improving environmental performance. These are regulation, consumer/supplier expectations, and internal safety needs, leading to factories' improved environmental performance through adopting and using a breadth of I4.0 technology. Increasing empirical evidence points towards many I4.0 technologies such as IoT, artificial intelligence and simulation reducing carbon emissions (Ghobakhloo, 2020a). Other I4.0 technologies have also been linked to reduced factory greenhouse gas emissions (Khan, Tabish and Zhang, 2023).

Environmental standards, regulations, and expectations from the public increasingly require factories to reduce their environmental footprint (Kassinis and Vafeas, 2006; Liu and De Giovanni, 2019). Pressure from external stakeholders to adopt practices and clean technology to improve environmental performance is rising (Kassinis and Vafeas, 2006). In this sense, adhering to environmental standards is linked to competitive advantage enabled by technology implementation (Dechant and Altman, 1994; Theyel, Merenda and Venkatachalam, 2001). The literature finds a proactive approach beneficial as managers need to predict sustainability regulation changes and customers' expectations about using clean production methods. Studies show that EP is best accomplished by preparing *"products, processes, and infrastructure for these [technology adoption] changes without sacrificing competitive advantage"* (Handfield et al, 1997). Additionally, most environmental regulations, such as ISO 14000, do not guarantee effective self-regulation. Broadening the I4.0 technology base resolves the issue of a factory circumventing toxic emission prevention (i.e., implementing energy technology) as the cost of pollution prevention is often more than paying the penalty for not complying with the emission standards and government mandates (Christmann and Taylor, 2001). I4.0 technology in conjunction with pressure from government regulations is expected to promote research and the implementation of environmental technologies to reduce emissions in the short and long term (Khan et al, 2022).

In summary, broadening the use of I4.0 technology has been widely shown to benefit environmental performance. Increasing empirical evidence about I4.0 technology used at the factory level to improve environmental performance supports this argument. More importantly, it has been shown that isolated I4.0 use (E.g., 3D printing), though reducing energy and waste, may increase environmental accidents and reduce the overall environmental performance if not used with other robotic, AGV, sensor, recycling, and protective technologies to minimise and spread the negative effects of some I4.0 technology. Broadening the use of I4.0 information technology can lead to the detection and analysis of resource consumption across production and supply chain processes to trace their carbon footprint (Gabriel and Pessl, 2016; Sarkis and Zhu, 2018; Bai et al, 2020; Sarkis, Kouhizadeh and Zhu, 2021). Moreover, unsatisfactory environmental performance is linked to changes in organisational structure, often leveraging technology, to improve sustainability collaboration among managers across different functions (Russo and Fouts, 1997; Russo and Harrison, 2005; Longoni and Cagliano, 2015). Given the rich empirical evidence on I4.0 technology minimising emissions, waste and energy consumption, environmental hazards, and accidents, it is hypothesised that:

H6: The capability to implement the breadth of a factory's I4.0 technology is positively related to the factory's environmental sustainability.

### *3.5.7 Breadth of I4.0 and Schedule Attainment*

There is increasing empirical evidence linking I4.0 technology to enhanced schedule attainment (SA) capabilities. The capability to implement the breadth of I4.0 is expected to benefit SA more directly due to increasing use of information technology within and across the organisation and the use of processing and automation technology (Azzone, Masella and Bertele, 1991). There are several streams of research supporting this hypothesis, revealing scheduling benefits from the adoption and use of a broad set of I4.0 technologies through the control of supply and demand variability as well as internal variability. Evidence of technology use, such as computer aided design (CAD), at the project level also reveals several negative effects on SA. For instance, SA is weakened if the I4.0 technologies implemented are incompatible with existing systems or if training is inadequate (Eisenhardt and Tabrizi, 1995). This could also be the case at the factory level, though prior evidence is overwhelmingly in support of factory managers' capability to implement the breadth of I4.0 technologies to improve SA at the factory. The capability of factory managers to implement the breadth of I4.0 is expected to mitigate expected and unexpected scheduling issues, as explored below.

The literature supports the notion that the less uncertainty there is with regards to future customer requirements, raw material and component availability, and internal processing times, the easier it is for a factory to adhere to the schedule (Mapes, Szwejczewski and New, 2000). Such uncertainty and complexity is caused by several diverse factors. Predictably, the number of products and product parts and the number of suppliers/customers impacts SA (Rossetti et al, 2023). Consequently, factories implementing ICT reduce internal complexity as well as supply chain complexity (downstream and upstream) to attain improved production scheduling (Bozarth et al, 2009). This could raise low SA, usually considered below 75%, to greater than 90%, which is considered high SA.

In addition to the predictable variations above, advanced production technology has been found to mitigate unexpected scheduling problems. Global disruptions such the recent Covid-19 pandemic caused unexpected supply issues, reducing raw material and production machinery availability and negatively impacted SA (Müller, Hoberg and Fransoo, 2022). In this context, information management is strongly linked to schedule attainment. At the factory, electronic data interchange (EDI) and E-information integration enable the prediction and mitigation of scheduling issues due to market unpredictability (e.g., seasonal demand), the complexity of the product (e.g., due to customisation), unexpected machine breakdowns, and the implementation of new technology (Ahmad and Schroeder, 2001; Molinaro, Danese, Romano and Swink, 2022). Similarly, enterprise resource planning (ERP) has also been found to enhance the on-time delivery performance and the ability to reduce lead times to meet schedules (McAffee, 2002; Cotteleer and Bendoly, 2006).

It is expected that broader use of I4.0 beyond manufacturing technology improves the capability to stabilise the master schedule, reduce variation in the process and enable better communication with suppliers to manage SA. For instance, factories can decide to receive and deliver supplies in small batches to circumvent scheduling issues with large batches. This also enables factory managers to avoid batching multiple customer orders into fewer production orders and prevent surplus capacity (Meixell, 2005). The breadth of I4.0 is also expected to improve the planning and decision-making process for SA as factory managers often make scheduling decisions monthly while revising and assessing goals annually (Gargeya, 2005). A lack of or limited breadth of information technology could lead to scheduling irregularity as the computation of SA is sometimes inconsistent across departments. Therefore, studies found coordination among the internal functions by means of vertical information systems to be beneficial in avoiding discrepancies in planning and calculating the schedule (Germain and Lyer, 2006). Expectedly, lower capacity due to a lack of machinery (e.g., breakdowns) causes scheduling issue for many factories. If the schedule is behind, the manufacturing execution system (MES) can address random variations by informing managers about relocating workers to low-capacity cells (Shoaib-ul-Hasan et al, 2018). Cloud-based ERP can enable greater maintenance management and visualise scheduling (Ghobakhloo and Fathi, 2019; Bonsa and Ivantury, 2022).

In summary, the capability of factory managers to implement the breadth of I4.0 technology can mitigate expected and unexpected factory scheduling issues. For instance, RFID can provide real-time information, yet (at a higher breadth of I4.0) IoT can address SA with optimisation algorithms while CPS's enable decentralised decision-making based on immediate and common scheduling data. Greater control over the breadth of I4.0 technology can cause a reduction in the workload on existing systems (e.g., MES) by relying on the combined effect or affordance of other technology, such as ERP used in combination with CPPS to decentralise scheduling based on ISA-95 and similar standards (Rossit, Thome and Frutos, 2019a; Rossit, Thome and Frutos, 2019b). Such a high level of production integration enables machine learning and the adjustment of sub schedules, such as material scheduling, to benefit from data based on consumption rates (Shurrab and Jonsson, 2022).

Such data could potentially advise factory managers to divert resources to slow moving bottleneck sections, which can occur in phased-out and phased-in zones. Given the evidence on many of the underlying I4.0 technologies improving schedule attainment, it is assumed that the capability to implement the breadth of I4.0 technology enhances schedule attainment. It is therefore hypothesised that:

H7: The capability to implement the breadth of a factory's I4.0 technology is positively related to the factory's schedule attainment.

### *3.6 Chapter Conclusion*

This chapter has introduced the main theoretical lens through which I4.0 is best viewed at the factory level. The chapter started by explaining the importance of dynamic capability and the orders of capability, which results in difficult to imitate competitive advantage. Secondly, the research model was explained as based on the core theory. This was followed by a definition of each part of the model and the interaction among the constructs in the model. Lastly, the hypotheses were worded based on the findings of studies in the same vein.

# Chapter 4. Research Methodology

### *4.1 Introduction*

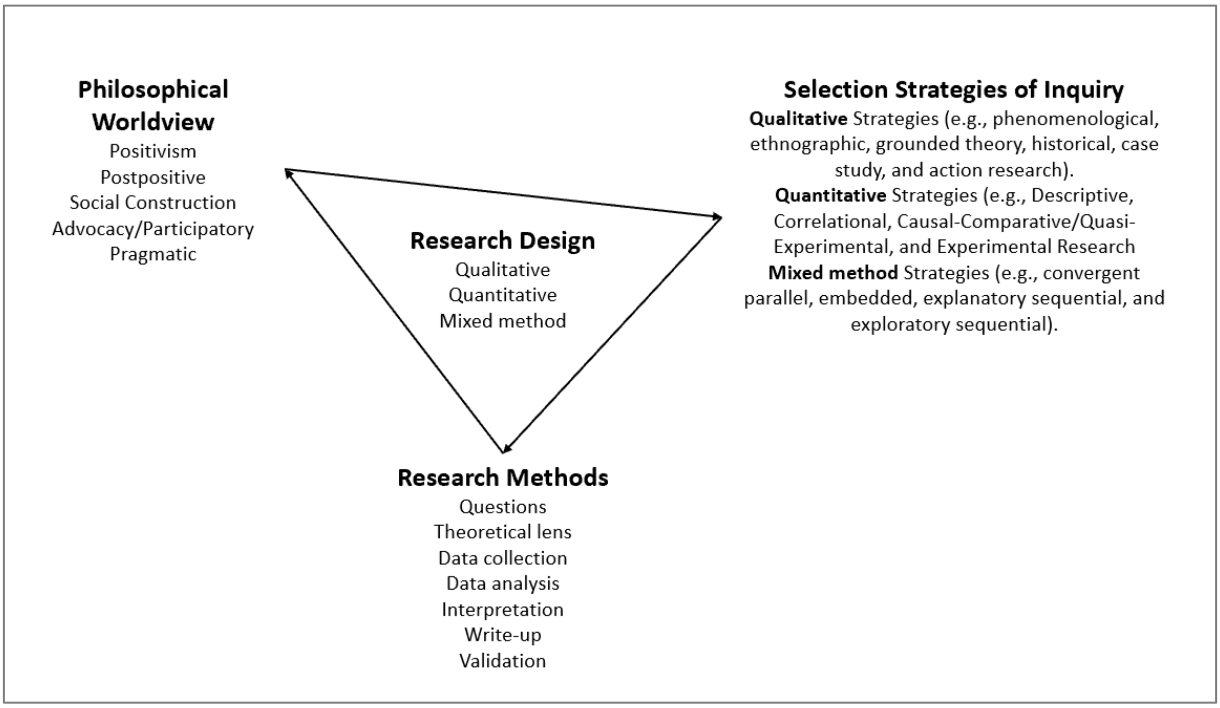
The methodology chapter initially explains the background to the research philosophy of the thesis. The subsequent sections explain the research design, variable selection and operationalisation, pilot testing, questionnaire administration, and data collection for the empirical survey. This includes variable and measure validity and reliability as well as questionnaire design. Lastly, the chapter sets out the general characteristics of the sample and discusses statistical analysis of the data, elaborating on the methods used to minimise sampling and non-sampling error.

### *4.2 Research Philosophy*

The research philosophy is defined as the set of assumptions, principles and beliefs the researcher shared in creating knowledge through the research process (Saunders, Lewis and Thornhill, 2009). The research method used (qualitative, quantitative, mixed) involves unique philosophical assumptions on the nature of reality and the perspective of the researcher (Creswell, 2014; Creswell and Plano Clark, 2017, p.23). When defining the philosophical research approach, it is important to understand what reality and being is (ontology), how knowledge is gained (epistemology), the research process (methodology), the values and ethics followed (axiology), and how the research findings are reported and presented (rhetoric) according to Creswell, J.W. and Creswell, J.D (2005) and Burrell and Morgan (2017).

Management researchers need to be aware of contradictory quantitative and qualitative paradigms while being aware of shifts in paradigms (Guba and Lincoln, 1994; Clarke and Clegg, 2000). For interdisciplinary fields that involve multidisciplinary researchers, such as I4.0, this is critical due to the fast growing and diverse literature. To test theory in management studies the researcher needs to overcome several practical and philosophical obstacles, identified as the *"complexity and contingency of social phenomena, imprecisely specified theories, the openness of social systems, and the unavoidability of untested assumptions"* (Miller and Tsang, 2011). Other similar studies further reinforce the essential nature of an appropriate philosophy for organisational and social research (Van de Ven, 2007, p.41; Bhaskar, 2010). Generally, there are two main paradigms emphasised in empirical social studies, which this thesis also followed: postpositivism and interpretivism. As shown in figure 4, the research design is shaped by the philosophical worldview of the researcher intertwined with the research methods and strategies of inquiry.

*Figure 4 Intersection of philosophy, strategies of inquiry, and specific methods, source: Creswell and Clark, (2017).*




The above is defined by Creswell and Clark, (2017, p.24) as the researcher's pursuit of understanding the *"philosophical worldview assumptions that they bring to the study, the strategy of inquiry that is related to this worldview, and the specific methods or procedures of research that translate the approach into practice"*. According to other authors, this philosophical worldview is defined as *"a basic set of beliefs that guide action"* (Lincoln and Guba, 1990, p. 17). These 'beliefs' stem from the researcher's own cultural background but are also formed by the research topic, advice and guidance received, and the setting in which the research is conducted (Guba and Lincoln, 1994; Lincoln and Guba, 2000).

Positivism is a philosophical framework that emphasises the use of scientific methods and empirical observation to gain knowledge. Positivist researchers can be defined as those who are seeking to establish universal laws and causal relationships in natural and social research domains, predicting outcomes based on observable regularities through objectivity and impartially verifying empirical evidence. Positivism is a relatively old philosophical framework, with research dating back to the mid eighteenth century, emphasising the stages of human intellectual development and the importance of social progress (Comte, 1853). Although criticism of positivism and scientific verification has been raised throughout the years in favour of falsifiability and conjecture (Popper, 1959), the bulk of the literature reinforces positivism. Most notably, Hempel (1965) emphasised how the positivist perspective reinforces the logical and empirical aspects of scientific explanation in social science. There are other limitations that make positivism an unsuitable research strategy for this study.

Logical neopositivism, or logical positivism, argue that the verification criterion for determining the meaningfulness of statements is based on empirical verification, observation, and logical analysis, rendering metaphysical claims meaningless (Brown, Stacey and Nandhakumar, 2008; Pierre, 2016). This view is more suited to basing I4.0 claims on available evidence as opposed to hype. As such, logical positivism adapts an inductive reasoning approach, which involves drawing conclusions based on observations and evidence. This philosophical view also places partial emphasis on theory, which supports theory building and theory testing in this field. Although logical positivism emphasises the analysis and elucidation of the logical structure of scientific statements and theories, the postpositivism view examined below places greater emphasis on subjectivity, theory, and the reflexivity needed to make sense of more complex I4.0 concepts and for clarifying the confusing and sometimes contradictory I4.0 terminology and semantics of the core concepts, which sometimes overlap with neighbouring literature.

Postpositivism acknowledges that scientific observations and empirical evidence verification are influenced by subjective factors, such as the researcher's perspectives, personal values, and biases (Panhwar, Ansari and Shah, 2017). This acknowledges that maintaining an objective view is unrealistic and that knowledge is, to some degree, socially created. Therefore, postpositivism, which this research is based on, encourages researchers to reflect upon their own assumptions and biases to determine the potential impact on the research process more transparently and purposefully. In I4.0 and social science in general, this mindset filters out hyped, overpromised, and frankly unrealistic expectations of what I4.0 projects at the factory involve. In contrast to positivism, which traditionally emphasises quantitative methods, researchers with a postpositivist view recognise the value of using multiple research methods to gain a comprehensive knowledge base on a complex phenomenon. As theory is significantly emphasised in postpositivism, often both qualitative and quantitative research methods are used to contribute to theory development. For instance, qualitative methods generate rich patterns, clarify terminology, and descriptions, and explore the particularities of social phenomena, while quantitative methods provide statistical analysis and test hypotheses during the inductive research process (Creswell, 2009; Creswell and Clark, 2017, p28; Morgan and Lacy, 2018; Timans, Wouters and Heilbron, 2019).

This strategy is adopted for this research to complement and balance the qualitative review of the literature and the opinions of the researcher about I4.0 with quantitative understanding and support for the complex causal relationships. Other philosophical frameworks, such as critical realism and pragmatism, were not aligned with the research goals of this study as external factors were not referred to and the underlying mechanisms and structures that generate the empirical phenomena were not the focus of the knowledge inquiry. Although not suitable at this level of investigating I4.0, critical realism could be more aligned with understanding underlying the social structures and mechanisms, economic, and organisational factors that influence the adoption and outcomes of smart factory technology. Conversely, this study was based on a postpositivism framework to emphasise causality among variables, theory testing and hypothesis verification and a reductionist approach, breaking down I4.0 implementation causes and consequences at the factory.

Interpretivism, as a philosophical framework in social research emphasises the importance of understanding social phenomena from the perspective of the individuals involved (Crotty, 1998). It acknowledges that social reality is constructed through human practices and interactions, and that meaning is contingent upon social constructions such as culture, language, consciousness, shared meanings, and instruments (Myers, 2019). In interpretivism, the researcher recognises the role of subjective interpretation and the influence of human interests in acquiring knowledge by studying social phenomena (Guba and Lincoln, 1994). This perspective contrasts with the objectivist view that social entities exist independently of social actors, and highlights the need to consider the context, values, and interpretations of individuals within a social context (Saunders, Lewis and Thornhill, 2009). Interpretivism encompasses various approaches such as social constructionism, phenomenology, and hermeneutics, which aim to uncover the subjective meanings and interpretations that underlie social phenomena (Collins, 2010). By adopting an interpretive philosophical framework, researchers can gain a deeper understanding of the social world and capture the complexities of human behaviour and social interactions (Crotty, 1998). Interpretivism focuses on understanding the subjective meanings and interpretations attached to social phenomena as opposed to underlying social structures and mechanisms. Incorporating an interpretivist perspective can help capture the individual experiences, perceptions, and attitudes of top-managers regarding broader use of Industry 4.0 technology, the higher-order capabilities needed, and performance outcomes. Qualitative methods, such as open-ended survey questions or interviews, can be used to gather rich insights into the factors affecting technology adoption.

### *4.2.1 Research Strategy*

Given the positivist and interpretivist philosophical approach to this research, the research approach and strategy was planned accordingly. Both deductive and inductive approaches are used in management research. In general, the inductive (interpretivist) approach is used to explore new insights, identify emerging themes, and gain a deeper understanding of the phenomenon under investigation, to provide rich descriptions of participants' experiences. On the other hand, the deductive (postpositivist) approach is used to test hypotheses based on existing theories and prior knowledge. A survey questionnaire can be designed with structured, closed-ended questions to collect quantitative data from a large sample of participants. Subsequently, the collected questionnaire data is analysed using statistical techniques to test the hypotheses and draw conclusions.

Management researchers are required to make conscious decisions on the philosophical approach and the research strategy they choose (Johnson and Clark, 2006). This mixed methods approach can lead to a comprehensive and holistic understanding of the research topic and enhance the validity and reliability of the study's findings (Onwuegbuzie and Leech, 2005; Fetters, Curry and Creswell, 2013; Fetters and Molina-Azorin, 2017). This mixed method research design is in line with empirical studies within novel research domains. For this study the approach was to initially explore, through a deductive approach, the still growing and crystalising literature on I4.0 and the sometimes-contradictory claims across the literature, followed by theory testing based on an inductive approach. The primary quantitative section of the research, as described, followed a web-based cross-sectional survey design. There are several advantages to survey research (Hair et al, 2010). Cross-sectional surveys allow researchers to collect data (e.g., opinions and behaviours) from a large sample of participants within a relatively short period at relatively low cost. Also, using appropriate sampling techniques and ensuring a representative sample, the researcher can make inferences about the broader population, enhancing the external validity of the findings. Cross-sectional survey design is well-suited for hypothesis testing in management research (Forza, 2002).

Given the postpositivist perspective, a cross-sectional survey design allowed the researcher to collect data from a sample of participants at a specific point in time (as opposed to longitudinal design). This approach can provide greater insights into the current state of Industry 4.0 implementation (the actual breadth), the antecedents to Industry 4.0 technology adoption, and outcomes at the factory level. Similarly, using a cross-sectional survey design within an interpretivist framework enabled the researcher to explore the perspectives, beliefs, and experiences of targeted individuals within the factory setting. Such a survey design provided both objective data and subjective interpretations on I4.0 (Modaresi, Asadi and Shadman, 2019; Liao et al, 2019; Braun et al, 2021).

### *4.2.2 Unit of Analysis and Respondents*

The unit of analysis for this study is the plant or factory level. Selecting the correct unit of analysis is widely prioritised in empirical research (Behling, 1978; Rousseau, 1985; Klein, Dansereau and Hall, 1994; Dansereau, Yammarino and Kohles, 1999). Due to the contingent approach to digital transformation in general, investigating I4.0 constructs at different levels and for different uses requires different methodological approaches. For instance, at the firm-level, a company may have multiple factories, each requiring a unique digital transformation approach. Particularly in relation to I4.0 the literature primarily focuses on the study of I4.0 at the organisation and firm unit-of-analysis (Nayernia, Bahemia and Papagiannidis, 2022). Analysing I4.0 with a broader, more encompassing, unit-of-analysis provides a holistic and wide-ranging view of the phenomenon yet fails to draw inferences on the finer more granular constructs and their implications, which are not easily generalisable or applicable to important sub-units. In this sense, *"plant-level results may be obscured or confounded at a higher level of analysis, such as the business unit (BU) or firm"* (Rosenzweig and Easton, 2010).

The main objective of the thesis is to relate factory capability to factory use of I4.0 technology, measured as the breadth of I4.0, and performance. Consequently, in operationalising variables related to manufacturing what is required is to select the unit-of-analysis that is most appropriate to the theory being tested and the literature limitations for the theory tested (Rosenzweig and Easton, 2010). For instance, given that the theory of dynamic capability is widely used for empirical research, studying routines, I4.0 use, and performance at the organisational level cannot be used by the researcher for inference at the factory level (Pentland and Feldman, 2005). Similarly, other too granular sub-units of analysis, such as project, group, asset, and individual units-of analysis, deviate from the aim of the study as they capture dynamic capability from different perspectives and only partially reveal factory implications. Consequently, studying dynamic capability and I4.0 at the factory level facilitates the granular analysis of dynamic capability compared to the overstudied organisational level, while addressing the aim of the study.

One senior factory manager was targeted as the primary respondent for each manufacturing factory participating in the sample. Considering the diverse nature of factories and the multitude of senior management roles, only top executive roles have been targeted, such as factory managers, directors, supervisors, and operations managers. Senior managers involved in the operations of the factory would be most knowledgeable and informed about the level of ordinary and higher-order capability, performance, and the breadth of I4.0 technology currently deployed at the factory. Top management would also be more competent about the average industry values for the performance measures, reducing response bias and error. Previous empirical studies have also obtained key informant insight at the factory from senior management (Gattiker and Goodhue, 2005; Swink, Narasimhan and Kim 2005). Similarly, within the domain of strategy at other levels, such as the SBU, key informants have been used to represent their unit (Zott and Amit, 2007; Wang and Zhang 2008).

### *4.3 Data Collection*

This survey followed the steps recommended by Forza (2002) as listed in Appendix C. Data was collected at two consecutive stages for this research. The initial stage collected data on the appropriateness of the model and the applicability of the variables via a set of interviews in the format of a pilot study. The second stage collected the main survey data from UK participants through a web-distributed questionnaire.

#### *4.3.1 Pilot Study*

The pilot testing stage included semi-structured interviews with both academics and high-ranking managers from a mix of multinationals considered as major I4.0 technology users and providers. Prior to the design of the survey model the researcher systematically reviewed the literature on previously published dynamic capabilities as potential antecedents to I4.0 as well as potential outcomes of I4.0. The comprehensive list of constructs was subsequently filtered based on fit with the main theory (higher-order capability selected), reliability values, unit at which the construct was measured (factory-level selected), and quality of the publication journal (High-ranking ABS-4* Journals selected). However, despite the filtering, dozens of potential constructs remained, including a mix of integration and collaboration capabilities, cultural and structural capabilities, HR related and social/relationship capabilities, and sustainability capabilities. The aim of the pilot study was to guide the researcher in distilling the remaining constructs into a compact and testable research model for theory testing (Hazzi and Maldaon, 2015; Malmqvist et al, 2019).

The five semi-structured interviews were all based on I4.0 technology, implementation methods and outcomes. The interviews were conducted with senior managers with previous experience in I4.0 projects and lasted 30-50 min (Zoom call). Prior to the interview the model and the questions were sent to each participant. The videocall interviews were recorded with permission and updated the researcher on the operational implications and antecedents relevant to the industry as opposed to merely designing the research model based on literature limitations. The interviewees were provided with the primary research model and definitions of the variables. They were asked about the relative importance of major I4.0 enablers/outcomes in the industry. An example of the interview questions can be seen in Appendix D.

Several constructs were eliminated and refined, such as for measuring the level of I4.0 at the factory only the breadth is measured. This is because piloting participants clarified the difficulty of measuring the I4.0 depth and other aspects, as in practice the use of advanced technology at other departments/factories is not necessarily known to the manager. Similarly, constructs relating to the sociocultural capabilities of the factory were deemed important for I4.0 yet not prioritised by industry decision makers for the breadth of I4.0 technologies. For instance, *"level of hierarchy", "Top-management support", "Employee satisfaction"*, and "employee loyalty" were removed from the model (Yee, Guo and Yeung, 2015; Hardcopf, Liu and Shah, 2021). Equally, in most interviews *"internal environmental management" and "external environmental management"* (Zhu and Sarkis, 2004) were deemed important but not considered an independent variable or a practical antecedent to I4.0 technology. Another important example is Lean and agile capability, not considered by the experts to be a necessary antecedent to every I4.0 implementation case but rather a lower-order capability, which the researcher can add as a control variable. More importantly, leanness and agility were identified in one interview as ordinary capability and not higher-order capability as they are easily imitable. On the other hand, constructs that did measure antecedents to I4.0 but were deemed by interviewees to overlap with other more complete, practical and relevant constructs were also removed. For instance, in measuring cooperation with others, *"customer relationship"* and *"supplier relationship"* (Royo-Vela and Velasquez Serrano, 2021; Schmidt et al, 2023), *"customer satisfaction"* (Bozarth et al, 2009) as well as constructs relating to inbound open innovation (Sisodiya et al, 2013), *"inter-organisational collaboration", and "interdependence with other plants"* were replaced by "systems integration" due to the latter construct measuring the relationship between the focal factory and all value chain partners not just technology providers (impacting the breadth of I4.0 technologies) or the provider of resources for daily factory operations to make products.

Other integration related factors were also highly recommended by the interviews, resulting in the researcher keeping "design-manufacturing integration" and "manufacturing strategy integration", as practitioners deem these capabilities critical for controlling costs and guiding business strategy during I4.0 implementation. Based on the responses from the pilot study the model was simplified and made specific for a better fit with theory and ease of empirical testing. A list of potential antecedents to I4.0B before the pilot testing and after the piloting is shown in table 4. Lastly, a list of the pilot study participants, their role, affiliation, and quoted response examples to the interview questions is shown in Appendix E.

*Table 4 Pilot testing Results*

| Variables Before the piloting | | Variables After the Piloting (Model) |
|---|---|---|
| **Independent Variable** | Openness and Experimentation | Design-Manufacturing Integration |
| | Design-Manufacturing Integration | Manufacturing-Strategy Integration |
| | Modular Design Competence | Systems Integration |
| | Manufacturing-Strategy Integration | |
| | Interdependence with other Plants | |
| | Technology Interdependence | |
| | Inter-organisational Collaboration | |
| | Contractual Definability | |

| | | |
|---|---|---|
| | Contractual Enforceability<br>Trust<br>Agility<br>Lean Production<br>Centralisation<br>Workforce Development<br>Systems Integration<br>Data Usage<br>Business Dependence on IT<br>Internal environmental management<br>External GSCM practices | |
| **Focal Variables** | The Breadth of I4.0<br>The Depth of I4.0<br>The Source of I4.0 | The Breadth of I4.0 |
| **Dependent Variables** | Automation<br>Flexibility<br>Cost<br>Schedule Attainment<br>Customer Satisfaction<br>Environmental Sustainability<br>Preventive Maintenance | Automation<br>Cost<br>Schedule Attainment<br>Environmental Sustainability |

### *4.3.2 Questionnaire Design and Format*

The design and distribution of the questionnaire is an important step following the previous steps. The questionnaire (See Appendix F) used a 7-point Likert scale to measure factory capability and performance, ranging from strongly disagree=1, disagree=2, somewhat disagree=3, neither agree nor disagree=4, somewhat agree=5, agree=6, strongly agree=7. For the breadth of I4.0, a binary measure was used as in previous studies (Büchi, Cugno and Castagnoli, 2020; Cugno, Castagnoli and Büchi, 2021; Cugno et al, 2022).

The format of the questionnaire and the way it is presented greatly impacts on the accurate presentation of the questions and collection of reliable data (Shemesh and Lazarowitz, 1988; Ergu and Kou, 2012). This also greatly impacts the response rate (Dillman, Smyth and Christian, 2009). Several considerations were taken into account by the researcher to guide the participants through the survey efficiently. The aim was to minimise distractions and clutter, present the questions in an easily readable font type and size and in a logical order. This will avoid miscommunication and misinterpretation of the questions and therefore minimise respondents' error rate. Several factors impacted the questionnaire format.

1. The questions were rearranged into a logical order. Only one question was presented at a time, with similar questions grouped into sections. The level of industry 4.0 (breadth of I4.0) was asked first as it is a binary measure and different from the remaining 7-point Likert questions. This also enabled the participant to respond without fatigue or confusion from previous questions. This was followed by question segments in relation to factory capability, factory performance, and personal information respectively. Lastly, the researcher included an end of survey page to ask for feedback and provide the participants with a completion code to verify submission and receive funds.

2. The questionnaire started with a welcome page, including a summary of the research and the purpose of the study. This initial page also allowed participants to enter their unique Prolific ID to verify the eligibility of the participants, allowing the researcher to keep track of the payment process more easily. The literature also supports having a welcome page regarding web-based social science research, which researchers often use to communicate clearly and efficiently with the participants (Fischhoff and Scheufele, 2014; Wong-Parodi, and Strauss, 2014).

3. All other questions (e.g., text, number input) were worded as concise and to the point close-ended questions (multiple-choice, Likert scale, yes/no) as opposed to open ended questions, which are more open to interpretation. In general, there was a mix of open ended (i.e., Product, industry) and close ended questions (Reja et al, 2003). In addition, the font type, size, spacings and consistency among similar sections was standardised. This enabled participants to use their usual laptop and personal computer as well as tablets and smart phones to respond.

4. Misleading and confusing questions, inadequate wording, personal questions were avoided (e.g., Gender and Religion). According to Forza (2002), the format sets the language of the questionnaire to be in line and consistent with the respondent's level

of understanding. The author states: *"If a question is not understood or interpreted differently by respondents, the researcher will get unreliable responses to the question, and these responses will be biased"*. In the same context, *"double barrelled"* ambiguous and partial questions, as well as emotionally phrased or loaded questions, were eliminated in order to prevent biased responses. The length of each question is also important in avoiding time waste and maintaining the respondent's attention. In general, questions exceeding 20-25 words were avoided (Converse and Presser, 1986; Lietz, 2010; Peytchev, and Peytcheva, 2017).

5. Appropriate response scales were used to match the (close-ended) questions with relevant response options (Dawes, 2008; Joshi et al, 2015). Specifically, for certain questions (factory capability, performance) a 7-point Likert scale was used, while for lists (i.e., the breadth of I4.0) a binary scale was used. This ensured that the correct type of scale measure (Nominal, Ordinal, Scale) was used to capture the data for each question type.

6. Pilot-testing of the questionnaire clarified sticking points for participants. Before the questionnaire was administered to the sample of the population, the questionnaire was distributed to 36 UK respondents to check the response rate and receive feedback on the clarity of the instructions and response options. During this stage the contact-administration protocol and measure quality were tested (Forza, 2002; Dillman, Smyth and Christian, 2009; Dillmann, 2011). It is important to note that this questionnaire pre-testing stage was conducted in addition to and after the main survey design pilot-testing, which aimed to operationalise the variables and define the model. This stage, however, enabled the researcher to conduct preliminary reliability testing and check the Cronbach's alpha (α) of each measure in the model. This feedback was used to fine tune the clarity of the instructions and questions.

This survey was distributed online and hence the data was collected via a web-questionnaire accessible only with an invitation link. There are several benefits to online questionnaires compared to phone, mail, and in person collection of data (Forza, 2002; Boyer et al, 2002; Dillman, Smyth and Christian, 2009). For instance, the cost and time needed for administering web-surveys is lower as only an internet connection and a phone or PC is needed (Pitkow and Recker, 1995). This method ensured a high response rate, accuracy of information, and it covers a large sample of the population as the data recording and storing is automatic, reducing data collection error. In contrast, mail distribution can often be blocked by companies' email filtering techniques, resulting in undelivered mail. Similarly, phone calls can be unanswered, go to voicemail or often be blocked by secretaries and assistants. Online questionnaires were also found to be more reliable in terms of completeness, particularly for sensitive and personal information (Forza, 2002).

For this research *"Qualtrics"* was used to format and write the questionnaire, generate a (URL) link to the survey, collect data, store the data, and for preliminary visualisation of the data. Qualtrics is a web service enabling the above through a well-designed and practical user interface. The researcher also used *"Prolific"* to distribute the survey link to the target sample. Qualtrics was linked with Prolific to initially filter and subsequently guide the participants through the questionnaire. This required participants to input a valid code to proceed from Prolific to the Qualtrics survey link and start the questionnaire. Similarly, participants were given a completion code at the end of the questionnaire and redirected back to Prolific to redeem funds. This enabled the researcher to view the data collection in real-time, checking that all Prolific ID's and completion codes were valid. Qualtrics also enabled the researcher to save the data in formats suitable for statistical analysis with SPSS, AMOS, Excel, and other formats. Section 4.8.1 further elaborates on the administration and distribution of the survey questionnaire.

The services provided by Prolific are widely used by government organisations (e.g., the European Commission), private firms such as Google, and academia (e.g.., Oxford University). There are an increasing number of social studies using Prolific.co (e.g., Dryhurst et al, 2020; Williamson, 2020; Anvari et al, 2022; Calabrese and Albarracín, 2023). There are several benefits to linking Qualtrics with Prolific. Most importantly, responses can be checked in real-time as they are completed, and invalid responses such as non-responses and mostly uncompleted returns were disregarded to minimise resource waste. The secondary benefit is the possibility of financially reimbursing the participants that fully completed the questionnaire, minimising the possibility of missing data. This is important as top managers are targeted who expect to be financially rewarded for their time, unlike junior management (Jobber, Saunders and Mitchell, 2004). The participants were reimbursed £10/Hour with most responses taking 15-20 min. Moreover, this allowed for the control of participants, ensuring participants' IP is recorded and that they can only take the test one time. This method of distribution is also beneficial compared to sending the (URL) link by email to potential participants because Prolific uses a large population database and automatically contacts/reminds the potential participants. In contrast, mailing requires the researcher to acquire contact details of top managers (adding costs), which still would not have guaranteed access to the managers or even a complete and returned questionnaire (Goldby, Stank and Vickery, 2001; Fleming and Bowden, 2009). This would have reduced the response rate. Consequently, using Prolific enabled more precise collection of higher quality data by simplifying the distribution process.

### *4.4 Sampling Procedure*

A sample is defined as a segment of potential respondents representing a much larger population. This is used by the researcher to make inferences and generalise the finings within the context of the larger population (Walters, 2021). The population refers to the entire group of potential respondents (people, firms, factories). Therefore, a correct sampling procedure and frame selection is very important for the researcher to statistically as well as theoretically relate the findings to the population. Two sampling methods are commonly used: non-random (judgemental) and random (representative) sampling, according to Cochran (2007). For this survey, random sampling was selected for the sample (in Prolific) to collect normally distributed data representative of the population.

To reduce the sampling error a sample with high capability to represent the population was carefully selected in Prolific. Based on Forza (2002), inadequate sample selection "*excludes the possibility of generalising the results beyond the original sample*" as it limits the use of more appropriate statistical techniques. Operations management research, though less frequently considering sample design, relies on a small sample size, with emphasis on sample credibility (Rungtusanatham *et al*, 2001). In this case, minimising sampling bias required the researcher to ensure samples were taken from multiple regions in the country as opposed to samples from limited geographical locations (cities in one county or region), which represent the population less. The sample procedure for this survey followed the steps of defining the population, clarifying the sample frame, sample size, defining the unit-of-analysis and the main respondents.

#### *4.4.1 Population*

To reiterate, the main objective of the survey is to measure factory performance and capabilities (lower-order and higher-order) and determine if the internal and external higher-order capabilities act as antecedents to the lower-order capability and performance. Therefore, the population is selected based on limitations in the literature and theory. Prolific includes a growing database of more than a hundred thousand potential participants in both the UK and the USA. For this survey the population of interest is the UK's manufacturing factory managers involved in I4.0 technology use.

#### *4.4.2 Sampling Frame*

The researcher selected the sampling frame based on the employment status, experience, industry, and employment sector. This ensured that the sample strongly represented the population of the UK's factory senior management. Several filters were applied to explicitly identify the sample. First, only full-time UK employees that are working in senior and executive management roles were selected. Second, the industry and employment sector was set to manufacturing, excluding other industries using I4.0. Third, using a short screening questionnaire, only participants with work experience at a manufacturing factory currently using I4.0 technology were admitted.

#### *4.4.3 Sample Size*

The size of the sample is a critical consideration for the researcher as collection of large data sets is costly, time consuming and requires unique considerations when conducting the statistical analysis. On the other hand, the sample needs to have an adequate number of cases (responses) to be meaningful and considered for statistical procedures, such as measurement quality assessment and theory testing (Forza, 2002). Sample size is determined based on the significance level ($\alpha$), which is the probability of making a type I error, and the statistical power ($1-\beta$), with Beta representing type II error. The latter occurs if the null hypothesis is not rejected when the alternative hypothesis is true. Table 5 illustrates the required sample size based on the effect or association strength, termed the *"size of the researched relationship"* (Forza, 2002). If a small effect is researched a much higher sample size is needed to obtain a higher statistical power, in contrast to researching a large effect. In OM research the effect size is fixed as the researcher cannot change the effect size of a phenomenon, in this case adopting and using the breadth of I4.0 technologies. Similarly, the significance level is usually fixed at 0.05 and 0.01. Therefore, the researcher only uses sample size to control statistical power (Verma and Goodale, 1995).

*Table 5 Sample size determination based on Forza (2002)*

| | Stat. power = 0.6 | | Stat. power = 0.8 | |
|---|---|---|---|---|
| | α = 0.05 | α = 0.01 | α = 0.05 | α = 0.01 |
| Large effect (e.g., strong association) | 12 | 18 | 17 | 24 |
| Medium effect (e.g., medium association) | 30 | 45 | 44 | 62 |
| Small effect (e.g., small association) | 179 | 274 | 271 | 385 |

Other studies have classified sample sizes for statistical analysis, such as structural equation modelling (SEM) into small (which includes 100 or less responses), medium having between 100 to 200 responses, and large sample sizes having over 200 responses (Kline, 2011. p309; Kline, 2017). This research uses a sample size of 320 factory managers. More importantly, the sample size is suitable for SEM, as average sample sizes greater than 200 are required for adequate SEM analysis (Shah and Goldstein, 2006). However, the sample size is not too great to burden the researcher with additional considerations while delivering a high statistical power ($1-\beta \geq 0.8$) to minimise type I and type II errors.

### *4.4.4 Response Rate*

The response rate is an important measure of the quality of the survey. It is a statistical measure of the number of full responses in terms of percentage (Fan and Yan, 2010). A low response rate can introduce errors in the estimates, even if the bias is modest (Forza 2002; Forza, 2016). This is because we do not know the bias level for non-responses. In social sciences the design elements of the questionnaire (e.g., length) and the online administration method impact the response rate (Forza, 2002; Kaplowitz et al, 2012). As described in the previous sections, the web-survey response rate was improved by specifying the population sample, having a comprehensive survey design including web distribution, and the use of incentives (Deutskens et al, 2004; Heerwegh et al, 2005; Smith et al, 2019). For instance, minimising open ended questions and providing adequate information increased the response rate of extant OM studies by more than 200% (as in the case of Sower, Motwani and Savoie, 1997; Ward et al, 1998). The literature broadly supports this and provides several other methods and techniques to improve the response rate for OM surveys (Flynn et al, 1990; Frohlich, 2002; Forza, 2016).

Previous OM surveys that targeted factory managers recorded a response rate of 37% to 56% (Ahire, Golhar and Waller, 1996; Flynn et al, 1994). Other social science research domains may require alternative methods, such as mailed surveys and phone calls, to achieve an adequately high response rate (Shannon and Bradshaw, 2002). However, for this study the initial stages of emailing and informing participants, survey distribution, and sending regular reminders were all automated by the web-based distribution platform. The response rate is a percentage function of the number of usable responses divided by the total sample minus any partial responses (Bell, Bryman and Harley, 2022). As of the fourth quarter of 2021, the total sample included 956 potential participants that were full-time employed in the UK manufacturing industry (n=458), and the UK manufacturing sectors (n=506). A total of 327 questionnaires were returned, with 7 questionnaires having missing data, which were deleted. Consequently, the remaining 320 full questionnaire responses resulted in a response rate of 34 percent. For theory testing OM studies, it is preferred to have the response rate above 50% (Flynn et al, 1990; Pinsonneault and Kraemer, 1993). Yet in this context, the value is within the acceptable limit as the survey was conducted during the covid-19 pandemic. The UK lockdown and disruptions lowered the average number of respondents willing to participate in questionnaire studies according to the UK Office for National Statistics (ONS, 2021). Other studies also reinforced this finding and identified *"survey fatigue"* as a major cause of reduced response rates during the pandemic (Rashid and Yadav, 2020; De Koning et al, 2021; Krieger et al, 2023).

#### *4.4.5 General Sample Characteristics*

The questionnaire was returned by 320 participants, each representing a manufacturing factory in the UK. Table 6 offers a summary of the characteristics of the sample. The sample is representative of small (55.3%), medium (17%) and large (27.8%) factories based on the number of employees. The majority of the factories are established in the market and are mostly older than two decades.

*Table 6 Sample Characteristics*

| Characteristics (Variable) | Category | % |
|---|---|---|
| **Factory Size (Employee number)** | 1-100 | 37.2 |
| | 101-200 | 18.1 |
| | 201-300 | 11.9 |
| | 301-400 | 5.0 |
| | 401-500 | 7.5 |
| | 501 or More | 20.3 |
| **Factory Age (Years)** | Up to 5 | 5.0 |
| | 6-10 | 11.6 |
| | 11-15 | 13.1 |
| | 16-20 | 15.0 |
| | 21 or More | 55.3 |
| **Production Sector** | Industrial Equipment / Heavy Machinery | 26.3 |
| | Food and Beverage | 11.6 |
| | Automotive | 10.0 |
| | Consumer Electronics and Electrical Equipment | 6.3 |
| | Chemical / Petroleum and Plastic | 5.3 |
| | Construction and Building | 4.4 |
| | Aerospace | 4.1 |
| | Pharmaceutical and Medical Equipment | 4.1 |
| | Metal | 4.1 |
| | Wood / Paper / Packaging and Printing | 3.8 |
| | Fabric / Clothing | 2.8 |
| | Other Manufacturing | 17.8 |
| **Participant Role** | Factory Manager / Supervisor / Leader | 47.5 |
| | Operations Manager / Supervisor | 24.4 |
| | Technical Manager | 10.6 |

| | | |
|---|---|---|
| | Quality and Safety Manager | 4.7 |
| | Other Top Management | 12.8 |
| **Sample Size** | | 320 |

The sample is also highly representative of the diverse spectrum of industries involved in the UK manufacturing sector. The highest response was received from factories producing industrial equipment and heavy machinery for industrial purposes (26.3%). Other strategic sectors such as the food industry (11.6%) and the automotive sector (10%) were also fairly represented in the sample. The participants mostly (71.9%) fit with the target sample, including factory and operation managers or supervisors. Only a small percentage (15.3%) included participants from technical and quality management and other top management employees (12.8%), identified as other top management at the factory, such as factory owners, chief executive officers (CEO) and other executive roles that are classified as top-management roles but may have varying terminology across different production sectors. A full list of the standard industrial code (SIC code) for the full sample is shown in Appendix G.

### *4.5 Variables and Measures*

Measuring the reliability of the constructs is critical for any research. In social science, such constructs can be measured and quantified as variables by assigning numerical values to the observations (Walsh and Lynch, 2018). In management research, studies have investigated suitable and applicable construct selection criteria across several management domains, for instance, variable selection and measurement for studies on supply chain management (Tangpong, 2011), information systems (Sethi and King, 1991), and strategic management (Boyd, Gove and Hitt, 2005). In general, studies emphasise the careful selection of variables through exact specification and definition of the constructs measured, ensuring content adequacy, and fit between constructs and the core theory of the research (Schriesheim et al, 1993; Petter, Rai and Straub, 2012; Nielsen, 2014). In practice, operationalising the variables requires variables to be measured on a scale and multiple questions (items) which need to be worded to best represent the theory, construct, and level of analysis of the study.

In management research, Likert scales are widely used for measuring variables for survey research, yet the appropriateness of using Likert scales is debated within the literature due to ambiguity related to the ranking order and distance between the scale options (Anjaria, 2022; Heo et al, 2022). Seven-point Likert scales were preferred to record the respondents' neutral perspective or mid-point (Chyung, 2017) and to give respondents enough freedom to express if they somewhat, mostly, or strongly agree or disagree with the items (questions/statements) that make up a variable. Conversely, while a 10-point Likert scale would have collected more detailed data the many response options would have complicated and obstructed reliable data collection and analysis (Dawes, 2008; Russo et al, 2021). In the context of technology implementation, seven-point Likert scales have been widely used for measuring capability (e.g., Letmathe and Rößler, 2022) and performance (e.g., Awan et al, 2021).

For this study all the variables are multi-item scales, carefully screened and selected from the existing literature, measured on a Likert scale of one to seven. The use of existing measures is encouraged for theory testing as more reliable and valid constructs can be selected by the researcher (Wouters and Sportel, 2005; Hair, Page and Brunsveld, 2019; Walsh and Lynch, 2018), while multi-item scales increase the reliability and validity of the construct (DeVellis, 2003). For a few variables, the level of analysis had to be changed since the construct had not been previously studied at the factory-level. As such, items were carefully reworded to fit the factory level. Also, some items have been changed from a five-point to a seven-point Likert scale to fit with the rest of the variables in the model and simplify the data analysis stage. It should be noted, however, that for the structural equation modelling, data from Likert scale measures are handled as an ordinal as opposed to a linear scale (Schumacker and Lomax, 2012; Awang, Afthanorhan and Mamat, 2016). Appendix H illustrates the measurement items of the model related to internal and external capability, the breadth of Industry 4.0, and factory performance.

### *4.5.1 Design-Manufacturing Integration (DMI)*

Design-manufacturing integration represents a core capability of any manufacturing organisation to coordinate and to some degree amalgamate the routines and practices of the design and manufacturing departments, normally operating in isolation (Swink and Calantone, 2004; Swink and Nair, 2007). Subunits such as individual factories with strong DMI can improve production agility (Zawadzki and Zywicki, 2016) and the quality of the manufactured product (Swink and Calantone, 2004; Turkulainen and Ketokivi, 2012). DMI was operationalised as an independent variable impacting (antecedent to) the breadth of I4.0 and was adopted from Swink and Nair (2007).

### *4.5.2 Manufacturing-Strategy Integration (MSI)*

Manufacturing-strategy integration represents the level of coordination and alignment between the strategy and manufacturing departments (Narasimhan, Swink and Kim, 2006). Such alignment is critical for communicating the core strategy for maintaining competitive advantage and business value (Machuca et al, 2011; Telukdarie et al, 2018). MSI also enables monitoring, scheduling, and control of tasks within the factory (Murugaiyan and Ramasamy, 2021). Manufacturing-strategy integration was operationalised as an independent variable impacting (antecedent to) the breadth of I4.0 by adopting the items from (Narasimhan, Swink and Kim, 2006).

### *4.5.3 Systems Integration (SI)*

Systems integration is defined by Barua et al, (2004) as the extent to which a firm, or in this case a factory, integrated various IT systems to provide visibility of customer and supplier data. This enables online information sharing and transaction across the value chain. This independent variable was operationalised by changing the firm to the factory level.

### *4.5.4 Breadth of Industry 4.0 (I4.0B)*

The breadth of industry 4.0 technologies measured the number of advanced industry 4.0 technologies deployed simultaneously. It refers to a first-order capability or ability of the factory to manage and orchestrate a diverse yet interconnected set of manufacturing technologies (Büchi, Cugno and Castagnoli, 2020; Cugno, Castagnoli and Büchi, 2021; Cugno et al, 2022; Bettiol et al, 2023). The breadth of I4.0 technologies was operationalised as the focal variable (dependent on the four higher-order capabilities and antecedent to performance) and measured ten technologies on a binary scale of either implemented or not implemented, adopted from Büchi, Cugno and Castagnoli (2020).

### *4.5.5 Automation Performance (AP)*

The level of automation performance is defined by the collection and access to production data (Ittner and Macduffie, 1995), empowering managers' decision-making capability (Jayasekara et al, 2022; Hughes et al, 2022). Automation performance was operationalised as a dependent variable and measured the level of automation for tool changing, job set up and preparation, the processing of a job or product, monitoring the production process, inspection process for less frequent checks, and material movement within the factory (Ritzman and Safizadeh, 1999).

#### *4.5.6 Production Cost Performance (CP)*

In manufacturing, cost control is attributed to the strategy and technology deployed (Boyer and Lewis, 2002; Achillas et al, 2017; Ward and Duray, 2000). Production cost was operationalised as a dependent variable and adapted from the factory-level study by Wong, Boon-itt and Wong (2011).

#### *4.5.7 Environmental Performance (EP)*

Adequate environmental performance is also required to ensure the reduction of emissions and adherence to guidelines and regulations (Kassinis and Nikos Vafeas, 2006; Liu and De Giovanni, 2019). Environmental performance was operationalised as a dependent variable adapted from Zhu and Sarkis (2004), changing the Likert scale from 5-points to 7-points, as with the remaining variables.

#### *4.5.8 Schedule Performance (SP)*

Adherence to the predetermined schedule is a competitive priority (Safizadeh et al, 1996; Netland and Aspelund, 2013), especially for factories increasing the operational complexity due to implementation of new technology (Rosenzweig, 2009) and increasingly complex supply chains due to the recent pandemic, for instance (Ge et al, 2022; Müller, Hoberg and Fransoo, 2022). This dependent variable was adapted from Bozarth et al, (2009) and only the scale was changed from a 5-point Likert to a 7-point Likert scale to maintain scaling consistency.

#### *6.5.9 Controls*

Factory size and production strategy defined the use of I4.0 and were controlled for testing the hypotheses. Studies commonly consider the organisation's size to be a defining and controlling factor for implementing technology and new processes (Netland et al, 2015; Lorenz et al, 2020). More importantly, industry 4.0 technology breadth is controlled by size based on the number of employees (Büchi, Cugno and Castagnoli, 2020; Cua et al, 2001; Fullerton and McWatters, 2001; Shah and Ward, 2003; Mellat Parast and Oke, 2022).

The production strategy also needs to be controlled in the model. Four different production strategies are classified by the literature, namely make-to-stock (MTS), make-to-order (MTO), assemble to order (ATO), engineer-to-order (ETO) (Olhager and Selldin, 2004; Lorenz et al, 2020). Each strategy includes certain benefits and drawbacks. A hybrid production strategy is also used (e.g., MTO/ETO), as in the case of Barbosa and Azevedo, (2018), yet for this research the production strategy was measured as a categorical variable.

### *4.6 Validity and Reliability*

The quality and legitimacy of the research findings relies on the appropriateness and quality of the research measures. In social sciences, particular attention is given to the design of the survey research to best represent the theory being tested. This includes careful consideration of the data collection process, comprising instrumentation and variable selection, validity checks of the selected constructs, and analysis of the data. Consequently, both the reliability of the constructs and the validity of the research define the quality and generalisability of the findings. As recommended by Forza (2002) and Rungtusanatham and Choi (2000), this is organised as a three-steps iterative process of initially checking face validity, followed by reliability assessment and construct validity assessment. The section below describes the research method used to minimise reliability and validity issues and improve the soundness and generalisability of the results. Chapter 5 elaborates on the statistics and values of reliability and validity for the variables in the model.

#### *4.6.1 Validity*

One of the major criteria for theory testing is the use of instruments and measures that have adequate internal and external validity. According to Forza (2002), the goodness of a measure can be determined by validity and reliability, defining validity as *"whether we are measuring the right concept, while reliability is concerned with stability and consistency in measurement".* Validity in survey research refers to the alignment of a set of instruments with the true concept, checking if items indeed represent and identify the concept intended to be measured within the broader framework of theory testing (Moore, Harrison and Hair, 2021). Checking the validity of potential concepts during the literature review stage improves the quality of the research and minimises the risk of erroneous data collection through selection of valid measures (Tharenou *et al,* 2007). Several types of validity can be checked to assess and ensure the quality of the measure and ensure the measure actually captures what was meant to be measured by the theory-based concept (Forza, 2002; Slater and Atuahene-Gima, 2004). For this study, validity was checked by assessing the face validity, content validity, construct validity (convergent and discriminant validity), predictive validity, and external validity. As examined in the next chapter, unidimensionality, construct validity and predictive validity are checked statistically by conducting confirmatory factor analysis (CFA) to determine convergent validity and analysing the average variance extracted (AVE) and using structural equation modelling (SEM) respectively (Forza, 2002; Slater and Atuahene-Gima, 2004; Becker, Rai and Rigdon, 2013).

Face validity, as the name implies, is a rather subjective evaluation of whether the operational definition of the construct was diluted and misshaped the measure, or if the measure clearly relates to what was meant to be measured (Hair, 2015). Forza (2002) argues that face validity is adequate if *"the measure 'on its face' seems like a good translation of the theoretical concept"*. As face validity is dependent on the researcher's judgment (Rungtusanatham et al, 1998), adequacy of face validity was ensured by systematically reviewing the literature on extant measures of a particular concept. Furthermore, this was ensured by carefully selecting the measures and ensuring that all the measures have been previously checked for validity and tested by research in high-ranking management journals, such as "*Journal of Operations Management*", "*Production and Operations Management", "MIS Quarterly*", "*Technological Forecasting and Social Change"*, and "*International Journal of Operations & Production Management".* Consequently, the researcher compared seemingly similar measures representing the same concept, yet with different operational definitions and wording. Measures operationalised at different units-of-analysis and based on alternative theories, as well as vaguely worded measures from low-ranking journals, were avoided in favour of using measures uniquely testing the dynamic capability theory. This enabled the researcher to simplify the selection of the extant measures with the highest face validity (i.e., the measure that represented the concepts of the theory best).

Content validity is a test to ensure that all of the items that make up a measure truly represent the concept (Churchill and Iacobucci, 2009). A variable with high content validity considers multiple aspects and dimensions of a concept, with the set of items directly representing the main concept. Rungtusanatham (1998) defined content validity as "the degree to which the measure spans the domain of the construct's theoretical definition''. It should be noted, however, that despite meeting the reliability criteria (see section 4.7.2) a measure can fail to meet the content validity criteria if it is multidimensional (i.e., items measure dispersed topics that deviate from the concept) (Anderson and Gerbing, 1988; Sekaran and Bougie, 2016). Furthermore, the concept of content validity is debated in the literature, particularly in social indicators research (Sireci, 1998; Forza, 2002; Bobko, Roth and Buster, 2007). In operations management research, studies often rely on the traditional content validity approach of focusing on the *"broader levels of the content domain and its relation to the test design"* while fewer studies examine content validity as *"the degree to which the content of a test appropriately represents its intended domain in terms of various criteria such as depth, breadth, or cognitive complexity"* (Sireci and Faulkner-Bond, 2014). Like face validity, the content validity has been maximised by thoroughly reviewing the literature and using high-ranking journals as the source of already tested and valid measures.

Construct validity is the most important measure of validity for theory testing (Bagozzi et al, 1991; Rungtusanatham and Choi, 2000). Forza (2002) defines a measure having construct validity if *"the set of items constituting a measure faithfully represents the set of aspects of the theoretical construct measured"*. Consequently, the focus is on assessing the alignment of the measurement questions with the main theory which is being tested (Hair *et al*, 2010; Hair *et al*, 2013; Hair *et al*, 2019). Construct validity is often assessed by checking the convergent and discriminant validity, the former checking the convergence between items of a construct and the latter checking separation between constructs. Convergent validity is achieved when items of the same concept are highly correlated. This is statistically checked through CFA to check for construct unidimensionality. Discriminant validity is achieved when two different constructs are statistically uncorrelated. This is statistically measured by comparing the square root of the average variance extracted (AVE) for latent constructs with the correlation between that construct and other constructs. A lack of discriminant and convergent validity represents inadequacy of the construct, or this could be an indication that the theory is unsuitable (Forza, 2002).

Predictive validity and concurrent validity are criterion related. Respectively, these are achieved when the measure has the ability *"to differentiate among individuals as to a future criterion"* and when *"the scale discriminates individuals who are known to be different"* (Forza, 2002). However, as both are criterion-related validity, only predictive validity is tested for this research (Forza, 2002). Two methods are widely used to establish the predictive validity. Nomological validity refers to how well the predictions of a construct are confirmed and if they positively correlate with similar constructs (Wang and Netemeyer, 2004). Alternatively, the internal validity can be an indication of predictive validity. Internal validity errors occur when the causal conclusion is *"less plausible than rival ones"* according to Forza (2002), leading to erroneous conclusions. Structural equation modelling (SEM) is used to determine the predictive validity, as examined in the next chapter.

Lastly, external validity refers to how well the results obtained from the research can be generalised across time and different settings (Tabachnick and Fidell, 2007; Drost, 2011) as well as findings among different individuals, groups, and occupations (Brutus et al, 2013). Improving external validity can broaden the audience for the findings of the research across similar research domains (Forza, 2002). Formal use of theory and using a standardised sample survey is also found to improve external validity (Scandura and Williams, 2000). Despite high levels of internal validity, maximising external validity can often lead to unclear and rather ambiguous causal relationships between the constructs, which can water down the findings in favour of generalisability (Aguinis and Bradley, 2014). This research focused on balancing both internal and external validity by ensuring the use of a sample survey and grounding the research model on an established and widely accepted theoretical lens from the literature. This allowed the researcher to measure and analyse the causal relationships in fine-grained detail and allow the results to be generalised.

### *4.6.2 Reliability*

Another important method to assess the quality of the measure is reliability. As explained in the previous section, a comprehensive review of the literature enabled the selection of valid and highly reliable measures from the literature. Reliability measures internal consistency and is defined as indicating the predictability, dependability, consistency, stability, and accuracy of the set of items that make up a measure (Kerlinger, 1986). This refers to the ability of the measure to yield the same results for repeated tests under the same conditions (Carmines and Zeller, 1979; Forza, 2002). There are several established methods measuring reliability, including the test-retest, alternative-form, split-halves method, and internal consistency method (Forza, 2002). Although some measures were assessed using composite reliability (CR) values (which exceed average Cronbach alpha values), this research used Cronbach alpha (α) values using the internal consistency method to assess reliability as it is analogous with CR and more widely accepted by scholars (Govindarajan and Kopalle, 2006; Field, 2009; Peterson and Kim, 2013; Cho and Kim, 2015).

For this research the use of other methods was limited for several reasons. For instance, the test-retest method calculates the reliability for the same measure and respondent collected at different periods in time (Brown et al, 2004). In essence, this is not very practical to assess the ability of the measure to maintain stability over time as for this cross-sectional survey the respondents are top factory managers and hence not likely to re-participate or remember their previous responses (Forza, 2002; Vaus, 2013). This may cause unexpected and often inflated correlation between the reliability of the items of a measure, masking genuine increase or decrease in reliability with erroneous data, which can inflate reliability values. The alternative-form method also administers the measure at two different points in time (e.g., separated by two weeks) to the same respondent. The alternative-form method assesses the *"equivalence of different forms for measuring the same construct"* (Forza, 2002). The split-halves method divides the items of a measure into two and measures and statistically correlates the responses for measuring the same construct.

In contrast to the above, the internal consistency method is more applicable for this research as it measures several aspects of reliability. Cronbach coefficient alpha, proposed by Cronbach, 1951), is a common test used for internal consistency to assesses the equivalence, homogeneity, inter-correlation of items comprising a measure. According to DeVellis (2005), CR (α) *"determine[s] inter-rater agreement when the ratings entail noncategorical data"*, which makes this method suitable for multi-item measures on a Likert scale. CR is widely used in operations management research and is calculated using average inter-item correlation and the number of items. Consequently, to maximise the reliability and (α) value, three strategies have been used. First, in order to minimise unreliability, the wording of the items and the question of the measure were carefully considered. Vague wording and incoherent use of technical terms reduces the reliability, as do incomplete or partial responses. Second, all of the measures use multiple items to improve reliability. According to scholars, at least three items should measure the theoretical construct using as few items as possible to avoid overlapping and confusing questions (Cronbach and Meehl, 1955; Peter, 1979; Vaus, 2002). Lastly, as mentioned before, the CR and the CR value of the items were carefully checked in the literature review process to select reliable measures. However, after the data collection, reliability (α) is measured and reported. Acceptable alpha values should be equal to or above 0.7 (although 0.6 is sometimes accepted), with values above 0.8 indicating good reliability (Nunnally, 1978; Forza, 2002, Taber, 2018).

A lack of validity or reliability could lead to several types of errors and *"disentangle the distorting influences of errors on theoretical relationships that are being tested"* (Bagozzi and Phillips, 1991). According to Forza (2002), a lack of reliability has the propensity to introduce random error, while low validity causes systematic error and bias. As discussed above, both reliability and validity were carefully considered before and after data collection to minimise measurement inconsistency and uncertainty, while improving the generalisability of the research findings (Wikman, 2006).

### *4.7 Data Analysis*

Data analysis for management surveys is often divided into two stages. Initially, the data is cleaned, and preliminary data analysis is conducted using SPSS and AMOS (both version 28) to acquire knowledge about the data characteristics (e.g., frequency distributions, correlations, central tendencies) and to conduct measurement quality assessment. This is followed by the second stage of the data analysis, conducting significance tests and checking the hypotheses (Forza, 2002). During the theory testing stage, the researcher was not merely considering the specific statistical test needed but also the interpretation of the statistical results to avoid statistical and internal validity errors.

#### *4.7.1 Exploratory Data Analysis*

During the first stage the data was cleaned, and personal information was separated from the main response data to maintain confidentiality and anonymity. Exploratory factor analysis (EFA) was used to explore the dimensionality of the constructs, assess the quality of the measurements, and examine the interrelationships among the items. In contrast to confirmatory factor analysis or CFA (conducted in stage two), in EFA factors are not assigned based on the underlying theory, rather the factors are derived from the data statistics (Hair *et al*, 2019). Principal component analysis (PCA) was used as the factor extraction method as the researcher was interested in checking the factor structure and maximum variance, as opposed to the common variance shared by the variables, which uses the Principal Axis Factoring (PAF) method. Subsequently, the factors were rotated to simplify the structure of the results and facilitate interpretation. In management studies, orthogonal rotation methods such as Varimax or Quartimax are commonly used. Varimax maximises the variance of factor loadings within each factor, while Quartimax maximises the sum of squared loadings (Treiblmaier and Filzmoser, 2010; Howard, 2023). In interpreting the results, the researcher examined three values. Specifically, the factor loadings indicated the relationship between each item and each factor, communalities represented the amount of variance explained by the factors, and eigenvalues represented the amount of variance explained by each factor (Hair, Page and Brunsveld, 2019; Hair et al, 2019). At this stage the researcher checked if the items load strongly (>0.8) onto a specific factor. Based on the theoretical and conceptual foundations and the size and significance of the loadings the researcher decided on retaining or removing items.

### *4.7.2 Confirmatory Data Analysis*

For the second stage, four main tests were conducted, including the initial reliability and validity checks as well as multiple regression and structural equation modelling (SEM). Construct validity (see section 4.8.1) was checked in AMOS using CFA. Initially, the model was drawn up, and maximum likelihood was selected as the estimation method. The data was interpreted based on fit indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Consequently, the researcher examined the standardized factor loadings to assess the strength and significance of the relationships between the latent constructs and the observed indicators. In addition, modification indices were considered to make any necessary modifications driven by theoretical justification. Similarly, convergent validity was checked by analysing the average variance extracted (AVE) values. An AVE value of 0.50 or higher indicates that at least 50% of the variance in the construct is accounted for by its indicators, which is considered acceptable for convergent validity (Hair *et al*, 2019; Cheung et al, 2023). Nonetheless, depending on the research field and the theoretical significance of the construct, lower values can be accepted. For instance, If AVE is less than 0.5, but reliability is good, the convergent validity of the construct could be adequate (Fornell and Larcker, 1981). The result of the CFA was interpreted based on common cut off values. CFI and TLI values above 0.90 are often considered acceptable, while values above 0.95 indicate a very good fit. RMSEA and SRMR values below 0.08 are considered acceptable, while values below 0.05 indicate a good fit. In addition to validity, the reliability (α) of the measures was also checked using SPSS (see section 4.8.2). All values were above the cut off threshold of 0.7, with some measures reaching a Cronbach alpha value of above 0.9, indicating very high reliability.

Multiple regression is a dependence approach to determine the value of one dependent variable based on multiple independent variables (Hair *et al*, 2019). To minimise the risk of type 1 and type 2 errors, the researcher checked certain assumptions on multicollinearity, linearity, normality, outliers, and homoscedasticity (Ganzach, 1998; Tabachnick and Fidell, 2007; Garson, 2012; Hair et al, 2019). Particularly for multicollinearity, occurring due to high correlation, the tolerance is required to be above 0.10, and the variance inflation factor (VIF) coefficient needs to be below the value of 10 for the constructs (Goodhue, Lewis and Thompson, 2017; Kalnins, 2018). For the research model tested in this study it was impractical to conduct only one regression as the model has multiple dependent variables. Consequently, the relation of the four antecedents to the breadth of I4.0 was tested using multiple regression. This was followed by multivariate multiple regression, testing the second part of the model with the breadth of I4.0 as the independent variable and the four performance outcomes as the dependent variables. Therefore, the breadth of I4.0 was designated as a dependent variable in the first regression and as an independent variable in the second regression.

Multiple regression determines the change in the dependent variable due to the independent variables, enabling the researcher to understand the specific contribution of each independent variable. On the other hand, multivariate multiple regression analysis examined the combined effect of the independent variable on all dependent variables simultaneously. However, in interpreting the results, the researcher considered the relationships between the independent variable and each dependent variable separately. For both regression analyses the researcher checked the regression coefficients, p-values, R-squared values, and other relevant statistics to reveal the relationship between the variables. For the multiple regression, according to Hair et al (2019), the regression coefficient (weights), or more commonly the standardised coefficients (β), is used as a statistical measure of the change in the dependent variable for a one-unit change in the corresponding independent variable, while holding all other independent variables constant. Positive coefficients indicate a positive relationship, while negative coefficients indicate a negative relationship, and the magnitude of the coefficients reflects the strength of the relationship. Lastly, regression analysis enabled the researcher to check for unexpected signs or significance, which could be an indication of endogeneity in OM research (Ketokivi and McIntosh, 2017; Hill et al, 2021). It is important to consider endogeneity in social research as it could lead to significant data misinterpretations due to high correlation with the error term or due to omitted variables, a measurement error, simultaneity, or reverse causality.

To test the research hypotheses AMOS SEM was used, which combines regression and factor analysis. SEM is a powerful statistical technique suitable for complex relationships among the variables (Hoyle, 2012; Hair, Ringle and Sarstedt, 2011; Hair, Gabriel and Patel, 2014). CB-SEM enabled the researcher to test the full theoretical model and conduct other tests such as confirmatory factory analysis (CFA). AMOS provided a user-friendly graphical interface that facilitated model specification and modification with easily modifiable path diagrams. The covariance-based SEM uses Maximum Likelihood (ML) as the estimation method, but other methods such as PLS-SEM are also suitable, though they may provide different values (Hair et al, 2021; Sarstedt et al, 2023).

Several reasons motivated the researcher to use maximum likelihood (ML) covariance based (CB) structural equation modelling (SEM). CB-SEM assumes that the observed variables follow a multivariate normal distribution, and it was preferred over PLS-SEM and other estimation methods due to the large sample size of this study. This is because the CB-SEM can handle violations of normality and other assumptions. Also, the ML-CB estimation method is more suitable for confirmatory studies based on large sample sizes that test theory using a factor-based model as opposed to exploratory analysis (Dash and Paul, 2021). ML is efficient for achieving the lowest possible variance among unbiased estimators in large samples. This estimation method provides consistent and unbiased parameter estimates, which converge to the true population parameters. ML-CB-SEM provides more rigorous and well-established model fit assessment measures, such as the chi-square statistic and fit indices such as CFI, TLI, RMSEA for better specification, estimation, and evaluation. These fit indices are not as extensively developed in GLS-SEM. The CB estimation method can also more effectively manage multicollinearity among the predictor variables by incorporating them into latent constructs, reducing the impact of collinearity on the estimates. These benefits allow the researcher to comprehensively evaluate how well the proposed model fits the observed data. In contrast, PLS-SEM traditionally relies more on prediction-oriented measures such as R-squared rather than fit indices. This method is widely used for similar empirical studies on industry 4.0 (Zott and Amit, 2007; Chauhan, Singh and Luthra, 2021; de Sousa Jabbour et al, 2022).

For the SEM, several cut off values are considered in order to accept or reject the hypotheses and determine the fit of the model with the data. The chi-square ($X^2$) statistic tests the divergence between the observed and expected covariance matrices. A non-significant chi-square ($p > 0.05$) value suggests a good fit, yet this is not considered as an ultimate measure of fit, as achieving a significant chi-square test result is common in large samples (Sharpe, 2015; Kline, 2015). Chi-square is reported in research relative to the degree of freedom (df). Ratio values ($X^2$/df) less than or equal to 2.00 are indicative of a very good fit between the model and the data (Byrne, 2016). The Comparative Fit Index (CFI) compares the fit of the hypothesised model with that of a baseline model (null model). A CFI with a value closer to 1 indicates a better fit, with cut off values of 0.90 as a minimum and values of indicative 0.95 as higher fit (Mia, Majri and Rahman, 2019). Similarly, the Tucker-Lewis Index (TLI) compares the fit of the hypothesised model with that of the null model, and again values closer to 1 indicate a better fit (Hair et al, 2019). Lastly, the Root Mean Square Error of Approximation (RMSEA) estimates the divergence between the hypothesised model and the population covariance structure. In this case, values closer to 0 indicate a better fit with RMSEA values of 0.08 or lower, indicating acceptable fit, and values of 0.05 or lower indicate a good fit (Chen et al, 2008; Xia and Yang, 2019).

### *4.7.3 Common Method Variance*

Common method variance (CMV) causes significant issues for the interpretation of the results. In management studies, CMV can cause inflated correlation and biased regression coefficients, which could mislead the researcher (Malhotra, Kim and Patil, 2006; Chang, Van Witteloostuijn and Eden, 2020; Bozionelos and Simmering, 2022). The main causes of CMV include methodological features of the survey, such as the wording of items and response scale format, which drives the covariance among the variables, as opposed to the underlying constructs, leading to inflated relationships among them. The aim was to mitigate this deviation in variance by carefully considering the wording of the questions, response scales, and other design issues identified during the questionnaire pilot study (see section 4.4) and put into practice during the questionnaire design (see section 4.9) (Podsakoff, MacKenzie and Podsakoff, 2012).

CMV was statistically checked during the preliminary data analysis using two methods, examining the loadings during EFA (see section 4.11.1) and Harman's single-factor test (Podsakoff et al, 2003). The latter test checked the eigenvalues and factor loadings of the first factor extracted. If the first factor explains a substantial portion of the variance and many variables load heavily on it, it may indicate potential CMV. Table 8 shows the result of the Harman's single-factor test, indicating a percentage variance of 20.59, which is below the 50% acceptance threshold (Podsakoff, MacKenzie and Podsakoff, 2012). Therefore, CMV was not considered an issue in this study.

*Table 7 Harman's One-Factor test*

| Factor | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 12.063 | 21.933 | 21.933 | 11.324 | 20.590 | 20.590 |

***4.8 Research Ethics***

Ethical considerations throughout the processes of primary data collection, data analysis, storage and data reporting constitutes an important aspect of survey studies in social science and management research (Sekaran and Bougie, 2016, p.159; Bell and Bryman, 2022, p.123). This required the researcher to take several measures to ensure adherence to ethical standards. Initially, the researcher submitted an ethical approval form, which was approved by the ethics committee of Newcastle University. Adhering to academic ethical standards during the research process aimed at improving the quality of the research data obtained, protect the rights of participants, and maintain the integrity of the research process (Broom, 2006; Crow et al, 2006).

Transparency was prioritised from the onset of data collection. Participants were precisely informed on the purpose of the study, who it is for and who may participate, what the data will be used for and who will use it, as well as the duration of the questionnaire. The welcome page provided the above information and a consent form, which allowed participants to choose if they would like to take part in the study by entering their PID. This enabled the researcher to obtain informed consent from each participant. Participants who needed more time to complete the questionnaire were compensated accordingly for the extra time, even if the questionnaire was completed in more than twice the expected time. This is because participants may not have completed the questionnaire under similar conditions and were therefore compensated fairly and equally. In addition, sensitive questions, which could have caused resistance by participants, such as exact factory performance and questions on gender, were deleted during the questionnaire design phase to avoid any unethical questions and the risk of alienating participants (Singer, 2018, p.79; Saunders, Lewis and Thornhill, 2019, p.178). More importantly, ethical screening of the questions ensured questions were not manipulated, inflated, or misrepresented, maintaining data accuracy and transparency.

Confidentiality and anonymity was also a critical consideration during transfer, data analysis and data storage (Cho and LaRose, 1999; Oberski and Kreuter, 2020). Confidentiality was maintained by ensuring that personal information such as location and PID's would not be released and kept separate from the survey response data. This was also supported by avoiding the unencrypted data transfer of personal information and examination of the data in aggregate. Therefore, only data at the group level was examined in the summary statistics. Similarly, anonymity refers to keeping the identity of the participants unknown. This ensured that participants' responses cannot be tracked back to the identity of the participants. In general, the data was anonymised after collection to avoid bias and adhere to anonymity guidelines, while the survey response data was kept confidential (Bryman and Bell, 2011).

### *4.9 Chapter Conclusion*

This chapter discussed the methodology used to respond to the two research questions mentioned in the introduction. Initially, the chapter explained the research philosophy and the research strategy. This was followed by examining the data collection method and sampling procedure. The operationalisation of the variables and measures was explained based on the research model. The final sections explained the methods used to assess the validity and reliability of the measures and elaborated the data analysis process. Finally, the research ethics and implications for transparency and confidentiality was explained.

# Chapter 5. Research Results

### 5.1 Introduction

The following chapter discusses the results of the data analysis stage of the study. Initially the chapter will discuss the screening process of the data, which includes identifying any outliers, checking homoscedasticity and multicollinearity. This is followed by confirmatory factor analysis and the multiple regression results. Lastly, the descriptive statistics and correlation results are shown, followed by the hypothesis testing results.

### 5.2 Data Screening

Screening the data is important to meet the criterion for accurate statistical analysis and correct interpretation of the results. This is because certain assumptions, such as the possibility of outliers, missing data, normality, homoscedasticity, linearity, and multicollinearity, need to be checked. This is the case for multivariate regression (Tabachnick and Fidell, 2007; Yoon and Millsap, 2007), both exploratory and confirmatory factory analysis (Osborne and Costello, 2009; Brown, 2015), as well as for structural equation modelling (Kline, 2015). This study used IBM SPSS version 28 to initially check for any reverse coded items. In this case one item was reverse-coded and no univariate outliners or missing data were observed. The screening of the data indicated that the constructs are linearly connected, and their variances are homogenously distributed. Lastly, the tolerance and variance inflation factor values were checked to confirm a lack of multicollinearity, as shown below.

#### *5.2.1 Missing Data*

Missing data can be a major cause of analysis manipulation and distortion of the results. Although cases with less than 10% missing data can be included in the study (Hair et al, 2010), half a dozen cases were missing more than 50% of the data and were deleted based on recommendations (Tabachnick and Fidell, 2007; Little and Rubin, 2019). However, due to the rigorous questionnaire design and distribution method, including addon web-tools (see chapter 4), participants were urged and indeed required to respond to each question before proceeding. This resulted in no missing responses or data from the completed questionnaires.

To confirm the lack of missing data, two tests were conducted. First, a frequency check was conducted in SPSS to check every variable. The results indicated no missing values for each of the variables across the 320 cases. In addition, a missing value analysis using expectation maximization (EM) algorithm to estimate missing data points, which is the preferred method for cases that experience little or no interdependency between the input variables (Nelwamondo, Mohamed and Marwala, 2007). The results again indicate no missing data for any of the cases, as illustrated in Appendix I.

### *5.2.2 Univariate and Multivariate Outliers*

Collected data can sometimes include responses that have extreme values on the variables (Schumacker and Lomax, 2004). These cases are classified as outliers and in extreme cases they can lead to distortions in the analysis, potentially inflating the mean, standard deviation, and correlation values (Tabachnick and Fidell, 2007). There are many reasons for the presence of outliers in the dataset, from errors in data collection, instrument error to partial survey instructions and inadequate design. Outliers are cases that differ from most responses and therefore need to be examined with care, explained or removed (Schumacker and Lomax, 2004; Field, 2009; Hair *et al*, 2010). The presence of such outliers should ideally be checked at both the univariate level, probing for extreme values on a single variable, and the multivariate level, to check for extreme values that impact two or more variables (Hair et al, 2010; Hair et al, 2014).

Based on the literature recommendations two methods were used to identify and check any univariate outlier, the IQR method and the more sensitive z-score method (Field, 2009; Field, 2013; Templ, Gussenbauer and Filzmoser, 2020). Initially, the interquartile range (IQR) was checked to make sure the range between the first quartile (Q1) and the third quartile (Q3) of the data that falls below Q1 - 1.5 * IQR or above Q3 + 1.5 * IQR is considered as a potential outlier. There were 471 potential extreme cases, yet all on the low the low side (see appendix I). The IQR method, however, is far less sensitive compared to the z-score method and therefore less strict in terms of classifying cases as having outliers (Templ, Gussenbauer and Filzmoser, 2020). Checking the more sensitive z-scores, which was calculated by dividing both skewness and kurtosis by their corresponding standard error, allowed for a more sensitive identification of outliers. Accordingly, the z-scores, also known as standardized values, need to be between ±3.29, with any cases exceeding these values in the positive or negative indicating outliers (Field, 2013). In total, six cases that showed a z-score of more than ±3.29, as well as several z-scores between ±2.0, which represented possible univariate outliers, were individually checked (See appendix J). These cases were kept, however, as explained below.

To check for multivariate outliers the Mahalanobis distance ($D^2$) is measure ford each case. The $D^2$ is a statistical measure of the distance between a point and a distribution in multivariate space while considering the correlations between variables in the dataset (Ghorbani, 2019). Distances that represent potential outlier cases are also relatively higher compared to other cases. Specifically, the p1 and p2 values illustrate cases with multivariate outliers, which have to be carefully examined. Several sensitivities are used in the literature to define the p1 and p2 values, which refer to the power parameters that can be used to adjust the sensitivity of the distance calculation. AMOS uses the Manhattan distance (p1 = 1 and p2 = 1), which is less sensitive to outliers, in contrast to the squared Euclidean distance (p1 = 2), yet adequate in this case. The default value of p2 = 1 indicates that the Mahalanobis distance is not statistically transformed to calculate the p1 and p2 values for the 320 cases.

The test results for multivariate outliers shown in Appendix J illustrate the Mahalanobis distances and p values for top cases with potential outliers. In the results table, the p1 values indicate the probability of $D^2$ exceeding the observed value, while the p2 values show the probability of the top largest with $D^2$ exceeding the observed value. Consequently, while small numbers of p1 are expected, values of p2 less than 0.001 are indicative of outliers (Hair *et al*, 2014). These cases were carefully and individually checked and found not to misrepresent the phenomenon being measured for several reasons. First, though extreme in value, the extreme responses were related to schedule attainment and strategy. Considering that data collection occurred during the Covid-19 pandemic, different scheduling performance and strategic priorities are expected across the range and type of factories in the sample. Also, the extreme cases, after individual review, were deemed acceptable in relation to the remaining cases in the dataset as the data is not too deviant from the remaining cases. Checking the role, experience, and other characteristics of the respondent further validated the quality of the data for these cases. Ultimately, deleting the most extreme cases did not significantly change the fit, with values dropping from (CFI=0.87, GFI=0.765, RMSEA=0.068) to (CFI=0.842, GFI=0.765, RMSEA=0.069), while no change in regression results was observed. As none of the cases indicated unusual responses they were kept in the dataset and not deleted, which also avoids selection bias and preserves the integrity of the data (Tabachnick, Fidell and Ullmann 2013; Hair et al, 2014).

### *5.2.3 Univariate and Multivariate Normality*

An important assumption for data analysis is normality of the data. Non normal data that is too skewed or kurtotic violates the parametric assumption of statistical tests such as regression and structural equation modelling (Hair et al, 2014; Zhou and Shao, 2014). Univariate normality is checked using the Shapiro-Wilk and Kolmogorov-Smirnov tests (Drezner, Turel and Zerom, 2010; Razali and Wah, 2011). If the p-value is greater than the chosen significance level (0.05), the null hypothesis is not rejected. This suggests that there is not enough evidence to claim that the data significantly deviates from a normal distribution. On the other hand, if the p-value is less than or equal to the significance level, we reject the null hypothesis. This implies that the data significantly deviates from a normal distribution, indicating non-normality. As shown in table 9, p-values are less than 0.05, indicating non-normality.

*Table 8 Univariate Normality tests (Kolmogorov-Smirnova and Shapiro-Wilk)*

| Tests of Normality | | | | | | |
|---|---|---|---|---|---|---|
| | Kolmogorov-Smirnova | | | Shapiro-Wilk | | |
| | Statistic | df | Sig. | Statistic | df | Sig. |
| **I4.0B** | .105 | 320 | <.001 | .962 | 320 | <.001 |
| **DMI** | .076 | 320 | <.001 | .977 | 320 | <.001 |
| **MSI** | .111 | 320 | <.001 | .956 | 320 | <.001 |
| **SI** | .124 | 320 | <.001 | .948 | 320 | <.001 |
| **AP** | .068 | 320 | .001 | .980 | 320 | <.001 |
| **CP** | .095 | 320 | <.001 | .973 | 320 | <.001 |
| **SP** | .125 | 320 | <.001 | .936 | 320 | <.001 |
| **EP** | .104 | 320 | <.001 | .935 | 320 | <.001 |
| **Factory Size** | .227 | 320 | <.001 | .801 | 320 | <.001 |
| **Production Strategy** | .352 | 320 | <.001 | .708 | 320 | <.001 |
| **a. Lilliefors Significance Correction** | | | | | | |

To check for multivariate normality, several methods were used. First, Mardia's Test was conducted, then the Q-Q plots were examined, followed by checking the skewness and kurtosis values.

Mardia's Test calculates the z-skewness and z- kurtosis for each variable. Acceptable results for Mardia's Test depend on the significance level (0.05) chosen by the researcher and the sample size (n=320). Generally, if the p-values associated with the test statistics are greater than the chosen alpha level, it is concluded that there is no significant evidence to suggest that the data deviate from multivariate normality (Mardia, 2004).

Results in table 10 found the p-values for skewness and kurtosis not to be significant (i.e., p-value<0.05), indicating that the data is significantly deviant from multivariate normality (Mardia, 1974; Byrne, 2010). Mardia's skewness value of zero indicates a multivariate normal distribution, while higher values indicate a more severe deviation from normality. In this case a value of 7.33 indicated moderate skewness. The expected Mardia's kurtosis value for a multivariate normal distribution of eight variables is equal to p*(p + 2) or 8*(8+2) =80 (Doornik and Hansen, 2008; Cain, Zhang and Yuan, 2016). The 91.8 value for kurtosis slightly exceeds the 80-cut-off value in this case, indicating a lack of multivariate normality. This is not problematic for this study, however, as p values above the threshold of $\alpha = 0.05$ are considered to be unproblematic even if the data is non-normally distributed (Lumley et al, 2002; Knief and Forstmeier, 2021). Moreover, ordinal data that measures responses on a Likert scale is expected to show some signs of non-normality as responses vary while categorical data does not require the assumption of normality.

*Table 9 Mardia's multivariate normality test*

| Mardia's multivariate skewness and kurtosis (N of Variables) | | | |
|---|---|---|---|
| | B | z | p-value |
| **Skewness** | 7.333052 | 391.096113 | 0 |
| **Kurtosis** | 91.803386 | 8.346255 | 0 |

Kurtosis values were checked to ensure that the items are not kurtotic, which can lead to inaccurate SEM results (due to deviating variances) given the maximum likelihood estimation method often used in AMOS (Yuan, Bentler and Zhang, 2005; Kline, 2011; Byrne; 2013). As shown in table 11, no variable is kurtotic, as values are far below the acceptable threshold of 7. In fact, some sources argue that kurtosis values between -2 and +2 are indicative of normally distributed data (George and Mallery, 2010). Skewness values are acceptable if they range between -1 and +1, which for large sample sizes is often considered acceptable. Some studies adopt a less strict skewness cut-off value of 3 (Finney and DiStefano, 2006), while others such as Hair et al, (2014) argue that both kurtosis and skewness values should be between -2.58 and +2.58. The tests suggest symmetrically distributed data, with no item strongly skewed to left or right. A stricter method to check for skewness is to check if the absolute value of the skewness is less than three times the value of the standard error, identifying four variables with skewed data, though within limits, due to varying factory capabilities and performance. This is also due to the large sample size, as larger sample sizes are more likely to produce significant (non-normal) results.

*Table 10 Descriptive Statistics*

| Descriptive Statistics | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Minimum | Maximum | Mean | Std. Deviation | Skewness | | Kurtosis | |
| | Statistic | Statistic | Statistic | Statistic | Statistic | Std. Error | Statistic | Std. Error |
| **I4.0B** | 0.00 | 10.00 | 4.8344 | 2.78724 | 0.112 | 0.136 | -0.853 | 0.272 |
| **DMI** | 1.00 | 7.00 | 4.9083 | 0.94176 | -0.567 | 0.136 | 1.117 | 0.272 |
| **MSI** | 1.00 | 7.00 | 5.2953 | 0.99460 | -0.869 | 0.136 | 1.322 | 0.272 |
| **SI** | 1.00 | 7.00 | 4.8219 | 1.27248 | -0.816 | 0.136 | 0.351 | 0.272 |
| **AP** | 1.00 | 6.67 | 3.5156 | 1.31198 | -0.132 | 0.136 | -0.706 | 0.272 |
| **CP** | 1.00 | 7.00 | 4.4891 | 1.31481 | -0.416 | 0.136 | -0.414 | 0.272 |
| **SP** | 1.00 | 7.00 | 5.0594 | 1.41241 | -0.797 | 0.136 | 0.101 | 0.272 |
| **EP** | 1.00 | 7.00 | 4.9599 | 1.38234 | -0.889 | 0.136 | 0.500 | 0.272 |
| **Factory Size** | 1 | 6 | 2.88 | 1.961 | 0.577 | 0.136 | -1.264 | 0.272 |
| **Production Strategy** | 1 | 4 | 1.67 | 0.949 | 1.267 | 0.136 | 0.459 | 0.272 |
| **Valid N (listwise) 320** | | | | | | | | |

The data shows signs of univariate normality based on acceptable skewness and kurtosis values. However, multivariate normality is an issue, as shown in Appendix K. Shapiro-Wilk and Kolmogorov-Smirnov tests, Mardia’s test and close analysis of the Q-Q plots revealed multivariate non-normal distribution of the data. This was the case even after deleting the top 10 to 30 most problematic (outlier prone) cases and repeating the tests, with negligible changes to normality test results. As explained above, this could be due to the large sample size, yet can be corrected statistically by using bootstrapping for SEM and regression. Bootstrapping creates subsamples from the original dataset set and uses resampling techniques that can greatly benefit non-normal data as it does not assume any specific distribution for the underlying data (Finney and DiStefano, 2006; Byrne, 2013). Other more stable SEM methods such as partial least square (PLS) also correct for lack of normality (Goodhue, Lewis and Thompson, 2012).

### *5.2.4 Linearity and Homoscedasticity*

Linearity and homoscedasticity are important assumptions for regression analysis to ensure adequate result validity and reliability. Linearity assumes that there is a linear relationship between the predictor (independent) variables and the dependent variable, which could explain proportional changes in the outcome variable directly due to change in the predictor variables (Hair et al, 2014). The Q-Q Plot (Quantile-Quantile Plot) was checked to ensure cases are close to the central line, indicative of normality. Appendix L shows the Q-Q plots for the variables, which compares the quantiles of the observed data with the quantiles of the expected distribution. For this study, all the cases are recorded near the central diagonal line, indicating normally distributed data.

Linearity assumption is met if the plots follow a linear line (Kline, 2011), which is the case for this study (See Appendix M). Homoscedasticity or constant variance assumes that the differences between the observed and predicted values is consistent across all the predictor variables. This assumption ensures that the model's predictions are unbiased and reliable. Unequal variance of residuals (heteroscedasticity) can influence the accuracy of hypothesis testing during SEM (Kline, 2011; Byrne; 2013). Therefore, to check for homoscedasticity the scatter plot is checked by plotting the residuals against the predictor variables. In this case the assumption is met as the points in the plot are scattered randomly around the zero line and do not form a clear pattern.

### *5.2.5 Multicollinearity*

The issue of multicollinearity occurs if two or more of the independent variables are strongly correlated (Shrestha, 2020; Vörösmarty and Dobos, 2020). Multicollinearity can lead to inflated standard errors (reducing the precision of estimates), reduced model stability and ultimately misleading interpretation of the importance of the predictions. Two values are often checked to assess the multicollinearity: tolerance levels and the variance inflation factor (VIF). Tolerance values below 0.90 and VIF values below 10 are considered as acceptable (Tabachnick and Fidell, 2007; Hair et al, 2010). None of the variables suffer from multicollinearity as both the tolerance and VIF values are within the acceptable range, as shown in Table 12.

*Table 11 Multicollinearity test (Tolerance and VIF)*

| | Construct | Tolerance | VIF |
|---|---|---|---|
| 1 | DMI | 0.740 | 1.352 |
| 2 | MSI | 0.595 | 1.681 |
| 3 | SI | 0.646 | 1.548 |
| 4 | AP | 0.667 | 1.500 |
| 5 | CP | 0.939 | 1.065 |
| 6 | SP | 0.778 | 1.285 |
| 7 | EP | 0.688 | 1.453 |
| 8 | Factory Size | 0.810 | 1.235 |
| 9 | Production Strategy | 0.954 | 1.049 |

The collinearity of the constructs was further analysed by checking the Condition Index and Eigenvalues. The Condition Index is a measure of multicollinearity among a set of predictor variables, with a large condition index indicating high multicollinearity. Similarly, the Eigenvalue indicates the amount of multicollinearity present in the data, with small Eigenvalues indicating high multicollinearity. Minimal collinearity is observed if CI < 30 and Eigenvalue > 0.01; collinearity is moderate if 30 < CI < 100 and 0.01 > Eigenvalue > 0.0001. High collinearity is observed if CI > 100 and Eigenvalue < 0.0001 (Alin, 2010; Hair et al, 2014; Aguirre-Ureta and Rönkkö, 2017; Kaur and Singh, 2019). Table 13 presents the collinearity diagnostics, showing that all Eigenvalues and Condition Index values indicate minimal collinearity.

*Table 12 Collinearity diagnostics*

| | | Model | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| **Eigenvalue** | | 9.181 | 0.285 | 0.227 | 0.081 | 0.070 | 0.048 | 0.042 | 0.034 | 0.017 | 0.015 |
| **Condition Index** | | 1.000 | 5.680 | 6.366 | 10.654 | 11.423 | 13.843 | 14.723 | 16.404 | 23.321 | 24.627 |
| **Variance Proportions** | (Constant) | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.01 | 0.05 | 0.01 | 0.05 | 0.88 |
| | DMI | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.19 | 0.03 | 0.60 | 0.15 |
| | MSI | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.04 | 0.00 | 0.65 | 0.30 |
| | SI | 0.00 | 0.00 | 0.00 | 0.00 | 0.05 | 0.00 | 0.02 | 0.89 | 0.02 | 0.01 |
| | Factory Size | 0.00 | 0.70 | 0.09 | 0.19 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 |
| | Production Strategy | 0.00 | 0.03 | 0.89 | 0.00 | 0.00 | 0.00 | 0.03 | 0.02 | 0.00 | 0.01 |
| | AP | 0.00 | 0.00 | 0.01 | 0.68 | 0.10 | 0.18 | 0.00 | 0.00 | 0.00 | 0.03 |
| | CP | 0.00 | 0.01 | 0.00 | 0.13 | 0.69 | 0.00 | 0.05 | 0.02 | 0.01 | 0.09 |
| | SP | 0.00 | 0.01 | 0.00 | 0.05 | 0.09 | 0.62 | 0.07 | 0.12 | 0.04 | 0.00 |
| | EP | 0.00 | 0.00 | 0.00 | 0.02 | 0.02 | 0.30 | 0.46 | 0.20 | 0.01 | 0.00 |

a. Dependent Variable: I4.0B

### *5.3 Confirmatory factor Analysis*

Confirmatory Factor Analysis is a statistical technique often used for analysing survey data, specifically for analysing the underlying structure of a set of observed variables (items) and to confirm the existence of the latent constructs (factors) that these items measure (Brown, 2015). It is an important step in the process of validating the model by checking if the variables are indeed indicators of the underlying latent constructs. Also, CFA identifies the number of latent factors that best explain the observed relationships among the variables, enabling item reduction if needed to attain better model fit (Hair et al, 2014; Hair et al, 2019). Due to the focus on factors in CFA it represents a measurement model in structural equation modelling. Ultimately, SEM uses a combination of such measurement models and structural models to test and validate the theoretical relationships between variables (Byrne, 2016).

#### *5.3.1 CFA Results*

The evaluation of the overall measurement model using various goodness-of-fit indices determines the fit of the model. The fit indices assess the extent to which the model can reproduce the observed data. A model with a good fit indicates a high level of consistency between the theoretical model and the empirical data, and it therefore does not require significant modifications (Kenny, 2015). If the model fit was inadequate, accurate and valid interpretation of the causal paths in the structural model would not be possible (Byrne, 2016; Hair et al, 2019; Kline, 2015). To this end, model re-specification can identify a better-fitting model that both statistically fits the data well and maintains practical and substantive theoretical implications (Marsh et al, 2004; Raykov and Marcoulides, 2018). During model re-specification it is important to balance the statistical adequacy of the model with theoretical coherence.

### *5.3.2 Goodness of Fit Results (Original Model)*

In line with the recommendations of Hair et al, (2010), the current study reports multiple fit indices to assess the model fit of the Confirmatory Factor Analysis (CFA) model. The fit indices include Chi-square (X2), Comparative Fit Index (CFI), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). By employing this approach, the researcher used both absolute and incremental fit indices. This aimed to provide a comprehensive evaluation of the model's goodness of fit, considering different aspects of model performance.

Specifically, CFI, IFI, and TLI values above 0.95 and RMSEA values below 0.08 are often considered indicative of good fit (Hu and Bentler, 1999; Brown, 2015). However, CFI, IFI, and TLI values above 0.090 and RMSEA values below 0.06 are acceptable (Hair et al, 2010). For the original model, the fit indices are: X2(1006) = 2032.209, P<.000, X2/df=2.0, IFI=0.869, TLI=.858, CFI=0.868, RMSEA=0.057. The results indicate acceptable RMSEA and X2/df values, yet the values of the incremental fit indices (CFI, IFI, TLI) are below acceptable levels, requiring re-specification of the model.

### *5.3.3 Model Re-specification*

There are several methods recommended in the literature to improve fit results. Some studies argue for the use of alternative or nested models (Schumacker and Lomax, 2012) and the use of an alternative estimation strategy, such as generalised least square (GLS-SEM), which does not assume multivariate normality (Henseler, Ringle and Sarstedt, 2015; Xing, Yuan and Bentler, 2019). Alternatively, model re-specification can be conducted to improve fit. Compared to the two previous methods, model re-specification may be preferred If theoretical justification for the modifications exists. For SEM in strategic management research, it is argued that *"alternative models should have been proposed a priori rather than making a posteriori changes"* (Shook, Ketchen and Hult, 2004).

Model re-specification involves iteratively modifying the model based on theoretical and empirical grounds. This is accomplished by adjusting factor loadings, error covariances, or freeing constraints on factor variances and covariances to improve the fit with the observed data (Bollen, 1989). In this case, first the loadings were checked, with observed variables deleted based on their contribution to the model's fit and theoretical relevance (Brown, 2015). This was followed by assessment of the residual matrix and modification indices.

The aim is to find a model that not only achieves acceptable fit indices but also aligns with the underlying DC theory and provides meaningful insights into the relationships between the latent constructs and observed variables (Marsh et al, 2004; Shah and Goldstein, 2006; Raykov and Marcoulides, 2018; Mia, Majri and Rahman, 2019). This was a careful process, with the researcher aware of *"the trade-offs inherent in transforming data"* (Shook, Ketchen and Hult, 2004). In this case the researcher followed the guidelines of Hair et al, (2010) to re-specify the model as follows:

**Step one: factor loadings assessment**

Examining the loadings can reveal the relationships between the observed indicators and underlying latent constructs. Factor loadings indicate the strength and direction of the relationship between each observed variable and the latent factor it is intended to measure (Byrne, 2001; Hair et al, 2010; Byrne, 2013). According to Hair et al (2010), the cut-off value of 0.5 was used to determine the strength of the standardised loadings. Respectively, three items scored a loading below 0.5 (DMI-6, CP-4, I4.0B-5, and I4.0B-6), as shown in table 14, which are potential candidates for deletion. Unlike the first two items and I4.0B-6, the fourth item (I4.0B-5) had a loading of 4.61, which is close to the 0.5 threshold. Therefore I4.0B-5 was not deleted despite the low loading due to three reasons. First, the breadth of I4.0 is a new construct in the literature and despite the high reliability values (see section 5.4.2) it is possible that for lesser-known technologies (in this case, cyber security and cloud computing) it indicates lower loadings and AVE values than expected. Second, it is important to maintain the total breadth of I4.0 technologies, if possible, in the final model to adhere to the underlying theory to be able to contrast the higher-order capabilities against a more complete set of I4.0 technologies.

Third, lowering the number of items for I4.0B will reduce the construct reliability. Lastly, as shown in the next step, deleting only DMI-6, CP-4, and I4.0B-6 was enough to notably improve the model fit.

*Table 13 Standardised factor loadings*

| Construct | Label | Factor Loading |
|---|---|---|
| Design Manufacturing Integration | DMI-1 | 0.653 |
| Design Manufacturing Integration | DMI-2 | 0.726 |
| Design Manufacturing Integration | DMI-3 | 0.686 |
| Design Manufacturing Integration | DMI-4 | 0.577 |
| Design Manufacturing Integration | DMI-5 | 0.511 |
| Design Manufacturing Integration | DMI-6 | **0.370*** |
| Manufacturing Strategy Integration | MSI-1 | 0.740 |
| Manufacturing Strategy Integration | MSI-2 | 0.610 |
| Manufacturing Strategy Integration | MSI-3 | 0.540 |
| Manufacturing Strategy Integration | MSI-4 | 0.691 |
| Manufacturing Strategy Integration | MSI-5 | 0.794 |
| Manufacturing Strategy Integration | MSI-6 | 0.854 |
| Systems Integration | SI-1 | 0.671 |
| Systems Integration | SI-2 | 0.782 |
| Systems Integration | SI-3 | 0.860 |
| Systems Integration | SI-4 | 0.786 |
| Systems Integration | SI-5 | 0.696 |
| Automation Performance | AP-1 | 0.663 |
| Automation Performance | AP-2 | 0.753 |
| Automation Performance | AP-3 | 0.773 |
| Automation Performance | AP-4 | 0.785 |
| Automation Performance | AP-5 | 0.734 |
| Automation Performance | AP-6 | 0.688 |
| Cost Performance | CP-1 | 0.834 |
| Cost Performance | CP-2 | 0.92 |

| | | |
|---|---|---|
| Cost Performance | CP-3 | 0.818 |
| Cost Performance | CP-4 | **0.414*** |
| Schedule Performance | SP-1 | 0.921 |
| Schedule Performance | SP-2 | 0.934 |
| Schedule Performance | SP-3 | 0.618 |
| Schedule Performance | SP-4 | 0.67 |
| Environmental Performance | EP-1 | 0.78 |
| Environmental Performance | EP-2 | 0.875 |
| Environmental Performance | EP-3 | 0.9 |
| Environmental Performance | EP-4 | 0.837 |
| Environmental Performance | EP-5 | 0.796 |
| Environmental Performance | EP-6 | 0.861 |
| Breadth of I4.0 | I4.0B-1 | 0.555 |
| Breadth of I4.0 | I4.0B-2 | 0.516 |
| Breadth of I4.0 | I4.0B-3 | 0.649 |
| Breadth of I4.0 | I4.0B-4 | 0.597 |
| Breadth of I4.0 | I4.0B-5 | 0.461 |
| Breadth of I4.0 | I4.0B-6 | **0.341*** |
| Breadth of I4.0 | I4.0B-7 | 0.535 |
| Breadth of I4.0 | I4.0B-8 | 0.514 |
| Breadth of I4.0 | I4.0B-9 | 0.577 |
| Breadth of I4.0 | I4.0B-10 | 0.635 |

**Step two: residual matrix assessment**

Standardised residuals reflect the discrepancies between the observed covariance matrix and the model-implied covariance matrix. Acceptable values for standardized residual covariances are typically small, indicating that the model provides a good fit to the data (Schumacker and Lomax, 2012; Byrne, 2013). Researchers can utilize modification indices based on these residuals to identify areas where model improvement may be needed (Kline, 2015; Byrne, 2016). Assessing the standardised covariance matrix in AMOS revealed only a few residual values higher than the 2.58 cut-off value but all were related to DMI-6 and CP-4, cases experiencing low factor loadings.

**Step three: Modification indices assessment**

Deleting three items with low factor loadings (DMI-6, CP-4) improved the model yet it did not meet the acceptance levels for the fit indices. Modification indices were checked to reveal paths that could potentially be freed to improve the model fit (Hair et al, 2014). Nonetheless, modification indices should be perceived judiciously and not be blindly followed without careful consideration and assessment of the factor loading and standardised residuals. Making modifications (freeing paths) solely based on high modification indices can lead to overfitting or model misspecification (Bollen, 1989; Schumacker and Lomax, 2004; Kline, 2015. p.285).

*Table 14 Modification indices*

| Error term (item) | | | M.I. | Par Change |
|---|---|---|---|---|
| **e42** | **<-->*** | **e43** | **133.091** | **1.321** |
| **e34** | **<-->*** | **e35** | **79.589** | **0.718** |
| e34 | <--> | e37 | 26.875 | -0.424 |
| **e32** | **<-->*** | **e33** | **26.819** | **0.217** |
| **e29** | **<-->*** | **e30** | **21.568** | **0.19** |
| **e31** | **<-->*** | **e32** | **21.408** | **0.231** |
| e11 | <--> | e12 | 20.755 | 0.216 |
| e62 | <--> | e63 | 18.631 | 0.089 |
| e37 | <--> | e38 | 17.283 | 0.34 |
| e29 | <--> | e33 | 17.108 | -0.166 |

a* Error terms correlated.

While precise thresholds may vary within the broader academic discourse, modification indices around 4.0 or above generally suggest a significant potential for enhancing fit by allowing the estimation of the associated path. Table 15 shows the three paths freed between the error terms for neighbouring items of performance constructs due to minor measurement item overlap. The five highest error term modification indices were correlated in AMOS, as shown in table 15. Most notably, freeing the first path between e42 and e43 in (M.I. = 133.091) improved the model fit by a notable margin.  Despite the option to free the path of one error term to two separate other error terms, the path between e34 and e37 was not freed due to a negative par change value, which indicated negative impact on model fit if freed. Similarly, the remaining error terms with modification indices above 4 were not correlated due to a lack of theoretical and empirical justification.

### *5.3.4 Goodness of Fit Results (Respecified Model)*

Based on the three-step model re-specification process explained above, three items were deleted (DMI-6, CP-4, I4.0B-6) and the paths between the error terms of three items were freed. The goodness of fit figures for the re-specified model are: X2 (871) =1396.53, P<.000, X2/df =1.603, IFI=0.930, TLI=0.923, CFI=0.929, RMSEA=0.043. As shown in Table 16, the model fit is significantly improved with acceptable fit indices but also aligns with the underlying DC theory and provides meaningful insights into the relationships between the latent constructs and observed variables in SEM (Shah and Goldstein, 2006; Raykov and Marcoulides, 2018; Mia, Majri and Rahman, 2019). The new model also indicated improved reliability and validity for the two constructs that had an item removed (DMI and CP), with I4.0B-6 showing a negligible 0.001 change in reliability due to the removed item.

*Table 15 Original model and re-specified model comparison*

| **Fit indices** | **Original model** | **Re-specified model** |
|---|---|---|
| X2 (df) | 2032.209 (1006) | 1396.531 (871) |
| X2 / df | 2.0 | 1.603 |
| IFI | 0.869 | 0.930 |
| TLI | 0.858 | 0.923 |
| CFI | 0.868 | 0.929 |
| RMSEA | 0.057 | 0.043 |

## ***5.4 Validity and Reliability***

As explained in chapter 4.8, reliability and validity are important measures of construct quality. Accordingly, construct, convergent, and discriminant validity, as well as reliability for the re-specified model, are shown and explained in the sub-sections below.

### *5.4.1 Construct Validity*

Construct validity is important in management research. It is critical to check if a measurement instrument effectively captured the underlying latent construct it aimed to measure (Hair et al, 2014; Hair et al, 2022). Convergent validity was first checked during the CFA and discriminant validity was checked by comparing the square root of the average variance extracted (AVE) for each variable with the correlations between that variable and all other latent variables (Meade and Lautenschlager, 2004; Sarstedt, Ringle and Hair, 2021). As explained in the previous chapter, this ensures that the observed indicators reflect the theoretical concept being studied.

Convergent validity examines the extent to which multiple indicators of the same construct converge and share common variance (Rigdon et al, 2021). Convergent validity was assessed using Confirmatory Factor Analysis (CFA) and checking the standardised regression weights. Factor loadings represent the strength and direction of the relationship between each indicator and the latent construct. Generally, Items associated with a construct with factor loadings above 0.7 indicate stronger convergent validity, while values above 0.5 indicate good validity (Hair et al, 2014; Hair et al, 2022). Table 17 shows the factor loading of the re-specified model, with all loadings at satisfactory levels and only one case (I4.0B-5) showing moderate yet still acceptable loading (0.441). Two reasons contributed to keeping this item. First, the measure related to cloud computing and as an important factory specific I4.0 ICT technology, the item contributed significantly to measuring a more complete breadth of I4.0 technologies. Second, Hair et al, (1998, p.112) indicate that a factor loading of 0.45 needs a sample size of 150 to be significant, or 350 for a factor loading of 0.30. Therefore, a factor loading of 0.441 is acceptable for the sample size of this study, which is 320. Other studies also suggest that a factor loading of 0.45 is fair (Comrey and Lee, 1992; Tabachnick and Fidell, 2007), while some even use 0.4 as the cut-off value for exclusion (Stevens, 1992).

*Table 16 Standardised factor loadings (Re-specified model)*

| Construct | Label | Factor Loading |
|---|---|---|
| Design Manufacturing Integration | DMI-1 | 0.681 |
| Design Manufacturing Integration | DMI-2 | 0.739 |
| Design Manufacturing Integration | DMI-3 | 0.668 |

| | | |
|---|---|---|
| Design Manufacturing Integration | DMI-4 | 0.501 |
| Design Manufacturing Integration | DMI-5 | 0.476 |
| Manufacturing Strategy Integration | MSI-1 | 0.742 |
| Manufacturing Strategy Integration | MSI-2 | 0.611 |
| Manufacturing Strategy Integration | MSI-3 | 0.541 |
| Manufacturing Strategy Integration | MSI-4 | 0.690 |
| Manufacturing Strategy Integration | MSI-5 | 0.793 |
| Manufacturing Strategy Integration | MSI-6 | 0.854 |
| Systems Integration | SI-1 | 0.670 |
| Systems Integration | SI-2 | 0.782 |
| Systems Integration | SI-3 | 0.860 |
| Systems Integration | SI-4 | 0.786 |
| Systems Integration | SI-5 | 0.696 |
| Automation Performance | AP-1 | 0.580 |
| Automation Performance | AP-2 | 0.690 |
| Automation Performance | AP-3 | 0.772 |
| Automation Performance | AP-4 | 0.823 |
| Automation Performance | AP-5 | 0.755 |
| Automation Performance | AP-6 | 0.696 |
| Cost Performance | CP-1 | 0.826 |
| Cost Performance | CP-2 | 0.933 |
| Cost Performance | CP-3 | 0.811 |
| Schedule Performance | SP-1 | 0.925 |
| Schedule Performance | SP-2 | 0.939 |
| Schedule Performance | SP-3 | 0.582 |
| Schedule Performance | SP-4 | 0.639 |
| Environmental Performance | EP-1 | 0.787 |
| Environmental Performance | EP-2 | 0.889 |
| Environmental Performance | EP-3 | 0.912 |
| Environmental Performance | EP-4 | 0.824 |
| Environmental Performance | EP-5 | 0.763 |
| Environmental Performance | EP-6 | 0.838 |

| | | |
|---|---|---|
| Breadth of I4.0 | I4.0B-1 | 0.562 |
| Breadth of I4.0 | I4.0B-2 | 0.527 |
| Breadth of I4.0 | I4.0B-3 | 0.642 |
| Breadth of I4.0 | I4.0B-4 | 0.584 |
| Breadth of I4.0 | I4.0B-5 | 0.441 |
| Breadth of I4.0 | I4.0B-7 | 0.538 |
| Breadth of I4.0 | I4.0B-8 | 0.524 |
| Breadth of I4.0 | I4.0B-9 | 0.581 |
| Breadth of I4.0 | I4.0B-10 | 0.638 |

Convergent validity is also evaluated by examining composite reliability, and average variance extracted (AVE). Composite reliability is a measure of the internal consistency of the indicators measuring a construct. It assesses the extent to which the indicators consistently measure the underlying construct. A composite reliability value above 0.7 is generally considered acceptable (Hair et al, 2022). Average Variance Extracted (AVE) quantifies the amount of variance captured by the indicators in relation to measurement error. AVE values greater than 0.5 indicate good convergent validity, revealing that the indicators collectively account for more variance in the construct than measurement error (Hair et al, 2022). As shown in Table 18, all measures indicate a CR value above the threshold, with most measures scoring above 0.86, while AVE is low for DMI and I4.0B, indicating weak convergent validity for these two measures yet strong reliability.

*Table 17 Reliability and validity (CR, AVE)*

| | CR | AVE | MSV | DMI | MSI | SI | CP | EP | AP | SP | I4.0B |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **DMI** | 0.772 | 0.409 | 0.272 | **0.639** | | | | | | | |
| **MSI** | 0.859 | 0.508 | 0.281 | 0.522 | **0.713** | | | | | | |
| **SI** | 0.873 | 0.580 | 0.281 | 0.345 | 0.530 | **0.762** | | | | | |
| **CP** | 0.893 | 0.737 | 0.088 | 0.007 | 0.113 | 0.126 | **0.858** | | | | |
| **EP** | 0.933 | 0.701 | 0.238 | 0.318 | 0.466 | 0.488 | 0.176 | **0.837** | | | |
| **AP** | 0.867 | 0.523 | 0.354 | 0.348 | 0.444 | 0.367 | 0.137 | 0.431 | **0.723** | | |
| **SP** | 0.863 | 0.621 | 0.234 | 0.316 | 0.464 | 0.484 | 0.296 | 0.354 | 0.346 | **0.788** | |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **I4.0B** | 0.805 | 0.317 | 0.354 | 0.436 | 0.356 | 0.356 | 0.100 | 0.423 | 0.595 | 0.197 | **0.563** |

Bold figures represent the square root of average variance extracted from the observed variables.

Off-diagonal: correlations between constructs

Discriminant validity checks whether the construct being measured is distinct from other related constructs (Roemer, Schuberth and Henseler, 2021; Hair et al, 2022). This was checked by comparing the AVE of each construct with the squared correlations between that construct and other constructs in the model. When the AVE of a construct is greater than its correlations with other constructs, discriminant validity is established. This is accepted for all measures except for I4.0B due to low AVE. In addition, maximum shared variance (MSV) measures the highest proportion of variance shared between any two constructs in the model. Acceptable values for MSV need to be below the AVE (Average Variance Extracted) of each construct to conclude discriminant validity. The rationale is that if the maximum shared variance is smaller than the average variance extracted for each construct, this indicates that the constructs are more distinct from each other than they are related. All measures are accepted except for I4.0B, yet this does not indicate a lack of validity. This is because an AVE value below 0.5 is accepted if composite reliability (CR) is greater than 0.6, indicating acceptable convergent validity of the construct (Fornell and David, 1981; Gefen, Rigdon and Straub, 2011; Lam, 2012; Henseler, Ringle and Sarstedt, 2015; Rönkkö and Cho, 2022). Therefore, despite the low AVE value for the breadth of I4.0 construct, the model indicated strong reliability (CR) and convergent validity and good discriminant validity.

*5.4.2 Construct Reliability*

To support the convergent validity and reliability (CR) test results of the previous section, the Cronbach Alpha of the measures is calculated and presented in this section for the original and re-specified model. The Cronbach Alpha value is assessed based on the internal consistency or reliability of a set of items (Tavakol and Dennick, 2011; Hair et al, 2020). A Cronbach Alpha value below 0.6 is deemed poor, a value greater than 0.7 is considered good and values greater than 0.9, though acceptable in certain circumstances, may suggest redundancy or duplication among the items (Hulin, Netemeyer and Cudeck, 2001; Sürücü and Maslakci, 2020). The Cronbach Alpha values of the original and re-specified model is shown in Table 19, showing all reliability values to be above 0.7, indicating strong to excellent reliability for all measures. Specifically, for DMI and CP the reliability of the measure improved notably after removing the final item for each measure.

*Table 18 Cronbach Alpha for original and re-specified model*

| Construct | Original model Cronbach's Alpha | Re-specified model Cronbach's Alpha |
|---|---|---|
| **DMI** | 0.739 | 0.762 |
| **MSI** | 0.852 | 0.852 |
| **SI** | 0.873 | 0.873 |
| **AP** | 0.874 | 0.874 |
| **CP** | 0.831 | 0.891 |
| **EP** | 0.935 | 0.935 |
| **SP** | 0.877 | 0.877 |
| **I4.0B** | 0.804 | 0.803 |

### *5.5 Hypothesis Testing*

This section presents the regression results used to check the hypotheses. The first part of the model examined the positive relation of the factory manager's integration capability on the factory's breadth of I4.0 technologies. This relation was tested using multiple regression. The second part of the model examined the positive relation of the breadth of I4.0 technologies on factory performance measures, representing competitive advantage. This was checked using multivariate multiple regression (Dattalo, 2013). The hypotheses are tested in this section and summarised in addition to the SEM results in the next section.

Combining the results of the regression analysis and SEM provides a more comprehensive understanding of the relationships, particularly for comparing complex models with a focal variable (Bollen and Pearl, 2013 p.301-328; Byrne, 2016; Kline, 2016). The regression results are also used to assess the robustness of the SEM results as the former analyses the two parts of the model separately and in more detail (MacCallum and Austin, 2000).

*5.5.1. Effect of integration capability on Breadth of I4.0*

The result of the multiple hierarchical regression is shown in Table 12 with the breadth of I4.0 as the dependent variable. The regression tests the first three hypotheses of the study, namely: (H1) higher levels of design-manufacturing integration are positively related to the breadth of I4.0; (H2) higher levels of manufacturing strategy integration are positively related to the breadth of I4.0; and (H3) higher levels of systems integration are positively related to the breadth of I4.0. This relationship was controlled by factory size and production strategy.

*Table 19 Dependent variable: Breadth of I4.0*

| | **Model 1** | **Model 2** |
|---|---|---|
| **Control Variables** | | |
| Factory Size | 0.335*** | 0.282*** |
| Production Strategy | 0.127* | 0.121* |
| **Independent Variables** | | |
| Design Manufacturing Integration | | 0.269*** |
| Manufacturing Strategy Integration | | 0.065 |
| Systems Integration | | 0.157*** |
| | | |
| $R^2$ | 0.148 | 0.290 |
| Adjusted $R^2$ | 0.138 | 0.279 |
| $R^2$ Change | 0.143 | 0.147 |

***, **, * indicate a significance level of .001, .01, and .05, respectively

*N* = 320. Standardised coefficients Beta (β) are reported.

As shown in Table 20, factory size was an important and significant control factor for the breadth of I4.0, with the following values for the first model (β = 0.335; t-value=6.358; p < 0.001). This strong relationship was also true even after adding the independent variables to the model (β = 0.282; t-value=5.719; p < 0.001). Production strategy, though to a far lesser degree, was associated with the breadth of industry 4.0, with values of β = 0.127; t-value=2.415; p < 0.016 for the first model and β = 0.121; t-value=2.489; p < 0.013 for the second model after adding the independent variables.

The first hypothesis was supported (β = 0.269; t-value=5.018; p < 0.001), showing design manufacturing integration to have a strong and positive relationship with the breadth of I4.0. This supports prior data on design manufacturing integration as a higher-order capability and antecedent to manufacturing technology implementation (Swink and Nair, 2007; Swink, Narasimhan and Wang, 2007). The second hypothesis was not supported (β = 0.065; t-value=1.104; p < 0.271), indicating not enough evidence to reject the null hypothesis. In other words, manufacturing strategy integration is not related to the breadth of I4.0 with low betta values and a p-value far greater than 0.05, showing strong non-significance. Consequently, manufacturing strategy integration is not found to improve the breadth of I4.0 technologies at the factory, which may indicate that this higher-order capability is more relevant to efficiency improvements such as leanness and agility rather than technology implementation (Narasimhan, Swink and Kim, 2006). The third hypothesis was supported (β = 0.157; t-value=2.899; p < 0.004), indicating that systems integration has a positive and significant relation with the breadth of I4.0, as further explained in Chapter 6.

### *5.5.2 Effect of Breadth of I4.0 on factory performance*

The results of the multivariate multiple regression (MMR) shown in Table 21 tested the second part of the model. In this section, H4 to H7 were checked to assess if they were supported or rejected.

*Table 20 Multivariate tests*

| | | Value | F | Hypothesis df | Error df | Sig. | Partial Eta Squared | Noncent. Parameter | Observed Power[d] |
|---|---|---|---|---|---|---|---|---|---|
| **Intercept** | Pillai's Trace | 0.824 | 357.335[b] | 4.000 | 305.000 | 0.000 | 0.824 | 1429.339 | 1.000 |
| | Wilks' Lambda | 0.176 | 357.335[b] | 4.000 | 305.000 | 0.000 | 0.824 | 1429.339 | 1.000 |
| | Hotelling's Trace | 4.686 | 357.335[b] | 4.000 | 305.000 | 0.000 | 0.824 | 1429.339 | 1.000 |
| | Roy's Largest Root | 4.686 | 357.335[b] | 4.000 | 305.000 | 0.000 | 0.824 | 1429.339 | 1.000 |
| **Factory Size** | Pillai's Trace | 0.057 | 4.627[b] | 4.000 | 305.000 | 0.001 | 0.057 | 18.509 | 0.946 |
| | Wilks' Lambda | 0.943 | 4.627[b] | 4.000 | 305.000 | 0.001 | 0.057 | 18.509 | 0.946 |
| | Hotelling's Trace | 0.061 | 4.627[b] | 4.000 | 305.000 | 0.001 | 0.057 | 18.509 | 0.946 |
| | Roy's Largest Root | 0.061 | 4.627[b] | 4.000 | 305.000 | 0.001 | 0.057 | 18.509 | 0.946 |
| **Production Strategy** | Pillai's Trace | 0.002 | .170[b] | 4.000 | 305.000 | 0.954 | 0.002 | 0.679 | 0.086 |
| | Wilks' Lambda | 0.998 | .170[b] | 4.000 | 305.000 | 0.954 | 0.002 | 0.679 | 0.086 |
| | Hotelling's Trace | 0.002 | .170[b] | 4.000 | 305.000 | 0.954 | 0.002 | 0.679 | 0.086 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Roy's Largest Root | 0.002 | .170[b] | 4.000 | 305.000 | 0.954 | 0.002 | 0.679 | 0.086 |
| I4.0-breadth | Pillai's Trace | 0.349 | 3.269 | 36.000 | 1232.000 | 0.000 | 0.087 | 117.679 | 1.000 |
| | Wilks' Lambda | 0.671 | 3.569 | 36.000 | 1144.714 | 0.000 | 0.095 | 119.965 | 1.000 |
| | Hotelling's Trace | 0.461 | 3.884 | 36.000 | 1214.000 | 0.000 | 0.103 | 139.809 | 1.000 |
| | Roy's Largest Root | 0.392 | 13.401[c] | 9.000 | 308.000 | 0.000 | 0.281 | 120.609 | 1.000 |

a. Design: Intercept + Factory Size + Production Strategy + I4.0Breadth_Res

**b. Exact statistic**

**c. The statistic is an upper bound on F that yields a lower bound on the significance level.**

**d. Computed using alpha = .05**

The test results indicated Wilk's lambda, Lawley–Hotelling trace, Pillai's trace, and Roy's largest root to be statistically significant for both the intercept and breadth of I4.0 technologies ($p < .001$) (Dattalo, 2013). It is therefore concluded that there are differences among the dependent variables as a function of the breadth of I4.0. Similar to the hierarchical regression in the last section, factory size is significant, while production strategy is not significantly related to the breadth of I4.0 technologies of the factory.

In MMR the sum of squares stands for Sum of Squares, representing the variability in the dependent variable that is explained by the predictor variable (breadth of I4.0). Similarly, the F-value is a ratio of the mean squares and tests the null hypothesis that the predictor variable does not have a significant effect on the dependent variable. Mean Square is the SS divided by the corresponding degrees of freedom. It provides a measure of the average amount of variability explained by the predictors. Lastly, the $R^2$ values are presented for each dependent variable. It is important to note, however, that the $R^2$ values for each dependent variable may not indicate the unique variance explained for that DV by the independent variable (breadth of I4.0) as a proportion of total variance explained for all DVs (Dattalo, 2013). Table 22 shows the $R^2$ value, SS, and F-value for each dependent variable.

*Table 21 Test between-Subject Effects*

| Dependable Variable | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| **AP** | 201.531[a] | 11 | 18.321 | 16.236 | 0.000 | 0.367 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **CP** | 19.138[b] | 11 | 1.740 | 0.802 | 0.638 | 0.028 |
| **EP** | 107.837[d] | 11 | 9.803 | 6.018 | 0.000 | 0.177 |
| **SP** | 22.677[c] | 11 | 2.062 | 1.035 | 0.415 | 0.036 |

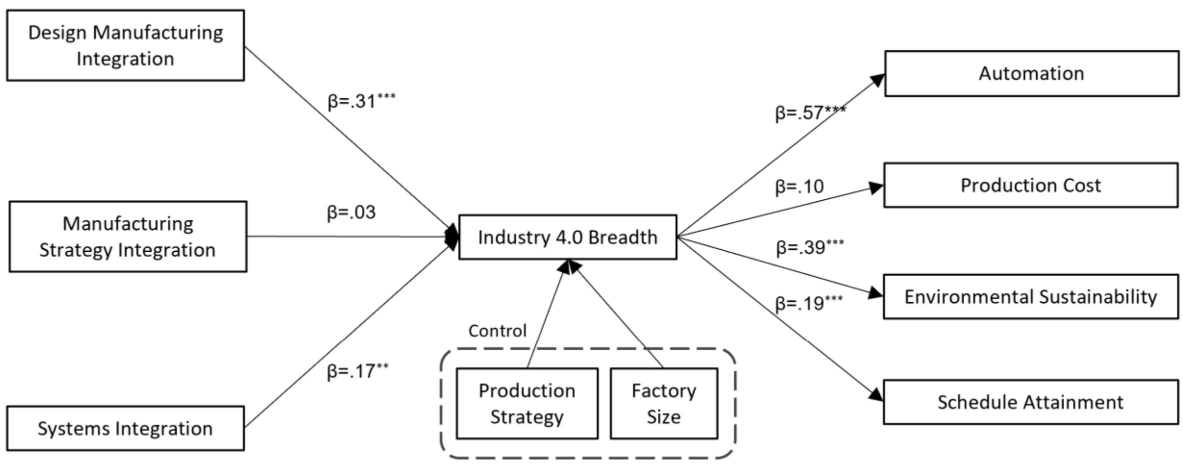
a. R Squared = .367 (Adjusted R Squared = .344)
b. R Squared = .028 (Adjusted R Squared = -.007)
c. R Squared = .036 (Adjusted R Squared = .001)
d. R Squared = .177 (Adjusted R Squared = .148)
e. Computed using alpha = .05

The results indicated support for (H4), showing the breadth of I4.0 to have a positive and significant impact on factory automation performance (SS=201.53, $R^2$=3.67, Adj $R^2$=0.322, F=16.23, p<0.000). The results for production cost performance indicated non significance and acceptance of the null hypothesis for H5 (SS=19.138, $R^2$=0.28, Adj $R^2$=0.007, F=0.802, p<0.638). The sixth hypothesis (H6) was supported, showing a positive and significant relation between Breadth of I4.0 and factory environmental performance, SS=107.83, $R^2$=1.77, Adj $R^2$=0.148, F=6.018, p<0.000. Lastly, H7 was rejected due to low significance, indicating a lack of support for rejecting the null hypothesis (SS=22.67, $R^2$=0.036, Adj $R^2$=0.001, F=1.035, p<0.415).

*5.5.3 Structural Regression Model (SEM) and Summary of the Hypotheses*

As the previous two sections analysed the model in two parts, structural equation modelling was conducted to test the hypotheses of the complete model, as shown in figure 5. Unlike the CFA, which analysed the measurement model, the SEM analyses the structural model. Similar fit indices were used to assess model fit, including chi-square, normed chi-square, CFI, P value, IFI, TLI, CFI, and RMSEA with similar cut-off values to CFA (Hu and Bentler, 1999; Niemand and Mai, 2018; Rappaport, Amstadter and Neale, 2020). The results of the SEM and the hypothesised relationships are summarised in Table 15. The model fit for the SEM achieved lower values in comparison to the measurement model during the CFA procedure. This is because of higher complexity among the measures of the structural model compared to the measurement model (Marsh, Hau and Wen, 2004). The fit for the structural model was X2 (651) =1293.2, X2/df =1.986, IFI=0.908, TLI=0.899, CFI=0.907, RMSEA=0.056. Although the IFI value was 0.001 point below acceptable values the remaining fit indices indicated good model fit.

*Figure 5 Research structural model and hypotheses (Standardised values)*




The reported SEM result in Table 23 was analysed based on the estimated path coefficient β value, critical ratio (C.R. is equivalent to t-value), and p-value. A t-value greater than or equal to 1.96 and a p value of ≤ .05 indicate significance of the path coefficient between predicator variables and outcome variables (Byrne, 2013; Schumacker and Lomax, 2016).

*Table 22 SEM results (unstandardised values)*

| **Hypotheses** | **Estimates (C.R.)** | **$R^2$** | **S.E.** | **Supported** |
|---|---|---|---|---|
| H1: DMI → Breadth of I4.0 | 1.199*** (4.056) | 0.275 | 0.296 | Yes |
| H2: MSI → Breadth of I4.0 | 0.06 (0.347) | | 0.175 | - |
| H3: SI → Breadth of I4.0 | 0.349** (2.660) | | 0.131 | Yes |
| H4: Breadth of I4.0 → AP | 0.206*** (8.273) | 0.324 | 0.025 | Yes |
| H5: Breadth of I4.0 → CP | 0.053 (1.758) | 0.010 | 0.030 | - |
| H6: Breadth of I4.0 → EP | 0.188*** (6.881) | 0.151 | 0.027 | Yes |
| H7: Breadth of I4.0 → SP | 0.099*** (3.318) | 0.036 | 0.030 | Yes |
| Factory Size | 0.381*** (5.956) | | 0.064 | |
| Production Strategy | 0.335* (2.539) | | 0.132 | |
| X2 (651) =1293.2, X2/df =1.986, IFI=0.908, TLI=0.899, CFI=0.907, RMSEA=0.056 | | | | |

*p < .05. **p < .01. ***p < .001.

The results of the structural equation modelling revealed that five out of seven hypotheses were supported. Regarding the antecedents to the breadth of I4.0, H1 and H3 were supported, showing a strong and significant contribution of design manufacturing integration and systems integration capability in relation to the breadth of I4.0 technologies. Conversely, H3 was not supported due to low statistical significance and therefore it can be concluded that there is not enough evidence to reject the null hypothesis in this case. Similar to the multiple regression results, industry 4.0 indicated a positive and significant relation with both automation performance and environmental performance, supporting H4 and H6 respectively. However, the breadth of I4.0 was not found to be positively and significantly related to cost performance, therefore rejecting H5. Unlike the regression results, the breadth of I4.0 was found to be positively and significantly related to schedule performance, supporting H7. There is further justification of why the hypotheses were supported, and more crucially why H2 and H5 were rejected, in the next chapter.

### *5.6 Bootstrapping Procedure Results*

Bootstrapping is a resampling technique that can be used to estimate the sampling distribution of a statistic, such as regression coefficients, factor loadings, or indirect effects. Bootstrapping can be useful when dealing with non-normal data or when the assumptions of traditional methods like Maximum Likelihood Estimation (MLE) are not met (Awang, Afthanorhan and Asri, 2015). Initially, the Bollen-Stine bootstrap p-value was tested for the null hypothesis that the sample data fits the population covariance matrix. A p-value above 0.05 suggests that the data fit the population covariance matrix well, implying that the assumption of multivariate normality is supported by the data. In this case the p-value (0.000) was below 0.05, suggesting that bootstrapping is not significant (Arbuckle, 2006). It should be noted, however, that the Bollen-Stine value is sensitive to large sample sizes (Gerbing and Anderson, 1992; Iacobucci, 2010; Kline, 2016). While a low Bollen-Stine p-value indicates that the data fit the population covariance matrix well, the data might still deviate from multivariate normality in ways not captured by this test. Bootstrapping was used for the regression in SPSS and for the SEM in AMOS, with 2,000 samples using the ML estimation method, and with 95% bias-corrected confidence intervals. Table 24 shows the standard error for the maximum likelihood model without and with bootstrapping. Table 25 shows the results of the unstandardised bias-corrected intervals. For the model the confidence intervals for the main paths do not include zero, therefore the null hypothesis cannot be rejected.

*Table 23 Comparison of bootstrap and ML standard errors –unstandardized estimates*

| Hypotheses | S.E. ML Estimates | S.E. Bootstrap Estimates |
|---|---|---|
| H1: DMI → Breadth of I4.0 | 0.296 | 0.298 |
| H2: MSI → Breadth of I4.0 | 0.175 | 0.178 |
| H3: SI → Breadth of I4.0 | 0.131 | 0.129 |
| H4: Breadth of I4.0 → AP | 0.025 | 0.026 |
| H5: Breadth of I4.0 → CP | 0.030 | 0.029 |
| H6: Breadth of I4.0 → EP | 0.027 | 0.026 |
| H7: Breadth of I4.0 → SP | 0.030 | 0.028 |

*Table 24 Bias-corrected confidence intervals –unstandardized estimates*

| Hypotheses | Estimate | Lower | Upper | P |
|---|---|---|---|---|
| H1: DMI → Breadth of I4.0 | 1.199 | 0.684 | 1.847 | 0.001 |
| H2: MSI → Breadth of I4.0 | 0.06 | -0.288 | 0.401 | 0.74 |
| H3: SI → Breadth of I4.0 | 0.349 | 0.085 | 0.589 | 0.01 |
| H4: Breadth of I4.0 → AP | 0.206 | 0.155 | 0.257 | 0.001 |
| H5: Breadth of I4.0 → CP | 0.053 | 0 | 0.111 | 0.048 |
| H6: Breadth of I4.0 → EP | 0.188 | 0.14 | 0.242 | 0.001 |
| H7: Breadth of I4.0 → SP | 0.099 | 0.042 | 0.153 | 0.002 |

### *5.7 Chapter Conclusion*

This chapter has provided a comprehensive view of the statistical results of the data analysis stage. The chapter started by explaining the process of cleaning and organising the data to prepare it for analysis. Confirmatory factor analysis (CFA) was done to show the goodness of fit for the measurement model and the process of improving the fit. Also, the validity and reliability of the measures was shown to be within acceptable levels. Lastly, the hypothesis testing results were shown for the multiple regression, multivariate multiple regression, and the structural equation model, which combined all parts of the structural model. Model fit was shown to be acceptable for the structural model. Five out of seven hypotheses were accepted based on the statistical significance.

# Chapter 6: Discussion

## *6.1 Introduction*

This chapter discusses the results of the research in line with the two research questions. At the factory sub-unit level, the use of the dynamic capability (DC) lens enabled the researcher to exemplify the significance and positive effect of important integration capabilities of factory managers to adopt and use sets of up to nine unique I4.0 technologies. Characterising the capacities of factory managers through the DC lens suggests that integration capabilities at the factory fit the attributes of second-order DC related to learning and the transformation of routines (routine changing routines). The study finds that the capability to implement bundles of complementary I4.0 technologies is related to adopting and using the breadth of factory I4.0 technology. These lower-order capabilities are found necessary but are easily copied by the competition. Two major gaps related to often difficult to measure factory capabilities and resources for competitive advantage are filled by this research, focusing on two research questions:

1. Can transformational integration capability of factory managers benefit the capability to implement the breadth of I4.0 technologies at the factory?

2. Does the capability to implement the breadth of I4.0 technologies at the factory lead to improved performance and competitive advantage of the factory?

This research adds to a promising but still narrow stream of management studies on dynamic capability and technology use at the factory level (Banker et al, 2006; Furlan and Vinelli, 2018; Hasegan, Nudurupati and Childe, 2018). This study is the first empirical research to relate second-order integration capability to the first-order capability of adopting and using the breadth of I4.0 technologies at the factory. It is also the first study of its kind to show factory managers' ability to adopt and use the breadth of I4.0 technologies to benefit competitive advantage across multiple factory performance indicators. In this vein, this study adds valuable empirical evidence at the level of the factory to research showing that first and second-order dynamic capability led to sustainable competitive advantage (Xiaosong Peng, Schroeder and Shah, 2011; Vanpoucke, Vereecke and Wetzels, 2014). Studies on second-order capabilities as antecedents to first-order capability for competitive advantage thus far mostly focused on firm and supply chain capabilities (Danneels, 2008; Aslam et al, 2020; Mikalef, Pateli and van de Wetering, 2021).

Table 25 illustrates the literature on the enablers to the breadth of I4.0 technologies. As shown in the literature review (see chapter 2), most studies focus on an isolated set of I4.0 technologies at the firm level. In contrast, at the factory level, only Cagliano et al. (2019) discussed the enablers to more than four I4.0 technologies. In response, this study measures a comprehensive list of ten I4.0 technologies and determines the importance of integration capabilities, which are seldom studied, as enablers to the breadth of I4.0 technologies. Similarly, the outcome of the breadth of I4.0 technologies are mostly studied at the supply chain and the firm levels (see table 26). However, at the factory level, only Battaglia et al. (2023) was found to study the impact of a wide range of I4.0 technologies on factory performance. Consequently, this study responds to this limitation and links the capability to implement the breadth of I4.0 technologies to measures of factory performance, which have been previously overlooked or taken for granted by scholars, such as the level of automation, production cost, environmental sustainability, and schedule attainment.

*Table 25 Literature on the enabler to the breadth of I4.0 technologies*

| | | Breadth of I4.0 technologies | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Level | Sources measuring enablers | CAD&CAE | IoT&IIoT | Cloud | BDA | ERP&MRP | RFID&NFC | Digital Twin | AR&VR | Blockchain | Sensors | AM | AI&ML | Robots | UAV | AGV | FMS&MES | EDI | Energy |
| Firm | Powell et al, (2024) | | ✓ | ✓ | | | | | | | | | | | | | | | |
| | Arcidiacono et al, (2022) | | ✓ | ✓ | ✓ | | | | | | | | | | | | | | |
| | Moyano-Fuentes, Sacristán-Díaz and Garrido-Vega, (2016) | ✓ | | | | ✓ | | | | | | | | | | | ✓ | | |
| | Saghiri and Mirzabeiki (2021) | | ✓ | | ✓ | ✓ | ✓ | | | | ✓ | | ✓ | | | | | ✓ | |
| | Lorenz et al, (2020) | | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | | | |
| Fa | Van Dun and | | | | | | | ✓ | | | | | | ✓ | | | | | |

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Kumar, (2023) | | | | | | | | | | | | | | | | | | |
| | Banker et al, (2006) | | | | | ✓ | | | | | | | | | | | ✓ | ✓ | |
| | Narasimhan, Swink and Kim, (2006) | ✓ | | | | | | | | | | ✓ | | ✓ | | | ✓ | | |
| | Demeter, Szász and Boer, (2017) | | | | | | | | | | | ✓ | | ✓ | | ✓ | | | |
| | Cagliano et al, (2019) | | ✓ | ✓ | ✓ | ✓ | | | ✓ | | | ✓ | ✓ | ✓ | | | ✓ | | ✓ |

*Table 26 Literature on the outcome of the breadth of I4.0 technologies*

| | | Breadth of I4.0 technologies | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Level | Source | ERP | IoT&IIo | Cloud | BDA | Digital | AR&VR | Blockcha | Sensors | AM | AI&ML | Robots | FMS&M | visualisati | Tracking | Outcome of Adoption |
| Supply chain | Liebrecht et al (2021) | | | ✓ | | | | | | | | | | ✓ | | Streamlining supply chain, cost reduction |
| | Yaroson et al, 2024 | | | ✓ | | | | | | | ✓ | | | ✓ | | Sustainable business performance, supply chain wellbeing |
| | Faruquee, Paulraj, Irawan, (2021) | ✓ | | ✓ | | | | ✓ | | | | | | | | Supply chain resilience |
| | Yang et al (2021) | ✓ | ✓ | ✓ | ✓ | | | ✓ | | | | | | | | Supplier digitisation leads to opportunism |
| | Sengupta, Dreyer and Jonsson (2024) | | ✓ | | ✓ | ✓ | | ✓ | | ✓ | | | | | | Supply chain planning for resilience |
| | Paolucci, Pessot and Ricci (2021) | | | | | | ✓ | | ✓ | | | | | ✓ | ✓ | Suppliers cost performance |
| Firm | Chavez et al (2024) | | ✓ | | | | | | | | ✓ | ✓ | | | | lean production |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bettiol et al (2023) | | ✓ | ✓ | ✓ | | ✓ | | | ✓ | | ✓ | | | | Depth of I4.0, creating knowledge to innovate processes and products |
| | Lorenz et al (2020) | | | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | | | Greater volume flexibility and lower production cost |
| | Büchi, Cugno and Castagnoli (2020) | ✓ | ✓ | ✓ | ✓ | | ✓ | | | ✓ | | ✓ | ✓ | | | Greater flexibility, speed, increased production capacity, decreased errors and costs, and an improved product quality and ability to meet customer needs |
| | Cugno, Castagnoli and Büchi (2021) | ✓ | ✓ | ✓ | ✓ | | ✓ | | | ✓ | | ✓ | ✓ | | | Greater perception of economic, knowledge, cultural, and system barriers and greater incentives |
| | Cugno et al (2022) | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | | Greater recovery from the Covid-19 pandemic |
| | Asokan et al (2022) | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | | | | Greater employment practices, health and safety, and business practices, quality of life and social welfare, social governance, and economic welfare and growth |
| | Dieste et al (2023) | | ✓ | ✓ | ✓ | ✓ | | ✓ | | ✓ | ✓ | ✓ | | | ✓ | Higher resource and energy consumption, higher material and production waste, and cost |
| Factory | Van Dun and Kumar, 2023 | | | | | | | | ✓ | | | ✓ | | | | Increased acceptance and ease of use of I4.0 |
| | Alavian et al (2020) | | | ✓ | | | | | | | ✓ | | | ✓ | | Higher throughput and number of parts produced, lower |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | | | | machine blockages and starvations |
| | Kumbhar, Ng and Bandaru (2023) | ✓ | | | | ✓ | | | ✓ | | | | ✓ | | | 10% throughput improvement |
| | Konur et al (2021) | | ✓ | ✓ | | | | | ✓ | | | | | ✓ | | Improved efficiency and consistency, reduced operational cost |
| | Tortorella Giglio and Van Dun (2019) | | ✓ | ✓ | ✓ | | | | ✓ | ✓ | | | | | | Operational performance gains |
| | Spaltini, Terzi and Taisch (2024) | | ✓ | | ✓ | ✓ | ✓ | | | | ✓ | ✓ | | | ✓ | Reduced non-recurring and recurring cost by 15% and 20% respectively |
| | Battaglia et al, (2023) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | Reduced time and cost, higher quality, productivity, new customer offerings, working conditions, and environmental performance |

In this study, this important yet rarely measured relation between the different types of capabilities is measured at the level of the factory, where the breadth of I4.0 technologies is mostly deployed in practice. This reveals interesting finer details and implications related to the management and reconfiguration of resources as well as the capabilities and practices that over time make up the routines of factory managers engaged in the digital transformation of the factory as markets change.

The results reinforce the notion that competitive priorities such as automation, schedule attainment, and environment performance shape the production technology adoption capabilities of factory managers. More importantly, we provide empirical evidence on such lower-order capabilities of adopting and using the breadth of I4.0 technologies to benefit from higher-order capabilities designed to transform and continuously update these practices, mechanisms, and routines, in response to changes in the market (Arcidiacono et al, 2023; Ali and Johl, 2023; Ed-Dafali et al, 2023).

### *6.2 Research Question 1: Can the transformational integration capability of factory managers benefit the capability to implement the breadth of I4.0 technology at the factory?*

The first research question sheds light on factory integration capability as antecedent to the capability of adopting and using the breadth of factory I4.0 technologies. It is clear that higher-order integration capability of factory managers is related to the transformation of factory resources, such as the I4.0 technologies used. The results contribute to clarifying the effect of second-order capability as antecedents to first-order capability as a competitive strategy (Danneels, 2012; Danneels, 2016; Teece, 2022). Specifically, this study adds to the literature on design-manufacturing integration (DMI), manufacturing-strategy integration (MSI), and systems integration (SI) capability. We show that these types of transformational capabilities lead to the capability to implement the breadth of factory I4.0 technologies. These I4.0 technologies include factory robotics, augmented reality, IoT, BDA, cloud computing, additive manufacturing, simulation technology, integration technology, and energy technologies. In this vein, we show that factories use four to five such I4.0 technologies on average if transformational integration capability is adequate.

It is apparent that integration capability viewed at the level of the factory involves the routines and practices of top factory managers, such as operations managers and factory supervisors. Unsurprisingly, manufacturing practices have been integrated with a variety of other business functions to gain a multitude of benefits, such as with marketing and sales (O'Leary-Kelly and Flores, 2002; Son et al, 2014), human resources (Santos, 2000), and procurement and supply chain management (Cagliano, Caniato and Spina, 2006; Chiarini, Belvedete, Grando, 2020). Yet these integration capabilities seldom relate to the priorities of the factory floor and the needs of factory managers during the I4.0 digital transformation.

By examining the breadth of I4.0 technologies through a dynamic capability lens at the factory we have shown that important higher-order integration capabilities, instead of relating to firm responsibilities (i.e., sales and marketing), closely relate to the operational priorities of the factory, such as production strategy and business strategy alignment, production friendly product design, and the coordination of upstream and downstream systems used throughout the value chain. What sets this research apart from the previous integration research is the characterisation and classification of design-manufacturing integration (DMI), manufacturing-strategy integration (MSI), and systems integration (SI) as higher-order or second-order dynamic capability. We show that these integration capabilities need to be selectively deployed as not all integration mechanisms and routines lead to greater use and protection of the factory's breadth of I4.0 technology. These capabilities are found to closely relate to transformational practices, routines, and mechanisms targeted towards the reconfiguration of existing resources, such as critical yet easily imitable factory production technology.

It is clear from the results that the capability of factory managers to adopt and use such I4.0 technology clusters and orchestration of these technologies for factory production connects the various functions and stages of manufacturing (Scott and Vessey, 2000; Frank, Dalenogare and Ayala, 2019). As is evident from chapter five, the sample of 320 UK factories implemented four to five distinct I4.0 technologies on average from a total of ten measured I4.0 technologies. Nonetheless, thus far the literature has not identified the antecedents and outcome of the breadth of I4.0 technologies (set of technologies) at the factory, while only a few studies were found to have investigated the breadth of I4.0 technologies for manufacturing firms (Büchi, Cugno and Castagnoli, 2020; Cugno, Castagnoli and Büchi, 2021; Bortoluzzi et al, 2022). This study specifically provides empirical results for the breadth of I4.0 technologies in response to this major limitation of the I4.0 literature.

As an example, one of the key advantages of I4.0 implementation is the ability to integrate Enterprise Resource Planning (ERP) systems with other critical factory components such as Advanced Planning and Scheduling (APS) systems, Material Requirements Planning systems (MRP II) and supply chain management systems (Davenport, 1998; Al-Mashari et al, 2003; Y.F. Chan and S.K. Chan, 2004). This capability of aligning technologies of two different functions is confirmed in this study as strengthening the managers' awareness of the tensions that may arise in the digital transformation. Therefore, factory managers with real-time access to a wealth of factory data, including customer information, product details, logistics and supply chain insights, can more comprehensively orchestrate sets of complementary I4.0 technology (Scott and Vessey, 2000; Tabim, Ayala and Frank, 2021). In this sense, the results of this study also indicate that data integration is a crucial component of developing the capability to manage the factory's breadth of I4.0 technologies, as it enables managers to leverage the data-driven decision-making needed for technology deployment and the optimisation of production in response to constant changes in the market (Mendoza, María Pérez, and Anna Grimán, 2006; Friederichet al, 2022).

The study specifically shows that design-manufacturing integration and systems integration improve the capability to unify disparate data sources and systems, found essential for achieving a cohesive and holistic view of factory operations (Markus, Petrie and Axline, 2000; Barua et al, 2004; Heim and Peng, 2010; Maiga, Nilsson and Ax, 2015). By integrating data from various parts of the product value chain, it is clear that factory managers can more efficiently streamline their processes, improve information flow, and enhance administrative and management decision-making as well as boost profitability (Markus, Petrie and Axline, 2000; Maiga, 2017).

Given the above, this study provides a valuable contribution to the I4.0 literature by measuring horizontal and vertical data integration technology, as well as the ability to manage eight other diverse sets of I4.0 technologies, including robotics, augmented reality, IoT, BDA, cloud computing, additive manufacturing, simulation technology, and energy technology. The investigated first-order capability of adopting and using the breadth of I4.0 is found to streamline production technology planning and shop floor control of these technologies to improve efficiency (Heim and Peng, 2010). This is because those factories are better positioned to unlock and ultimately shield the additional value gained from using the breadth of I4.0 technologies, as opposed to factories deploying only data resources across the production line or in silos across the factory (Gattiker and Goodhue, 2005; Banker et al, 2006). In effect, this study shows that factories incorporate new production systems more easily and adhere to technology standards more consistently if the factory managers' capability to control the breadth of I4.0 is adequate. Such managers can better deal with the growing commercialisation of more diverse I4.0 technologies, which need to be well understood and optimised in the factory environment to be used to their full potential (Willcocks, Feeny and Olson, 2006; Chiarini, Belvedere and Grando, 2020). This study shows that the first-order capability of adopting and using the breadth of I4.0 is best protected from imitation if it is driven by the factory specific higher-order integration capability.

We have shown that dynamic capability is a critical component for smart factory readiness. The development of comprehensive roadmaps enables factory managers to systematically advance the use of technology (Chatterjee et al, 2002; Larkin, 2017; Črešnar et al, 2020; Liebrecht et al, 2021). These findings are invaluable for proactive I4.0 planning, ensuring that factory resources are allocated effectively to best gain competitive advantage by improving schedule attainment performance (SP), environmental sustainability performance (EP), and a level of automation performance (AP) at the factory (Xiaosong Peng, Schroeder and Shah, 2011). The results show that integration does not only benefit the utilisation of sets of I4.0 technologies but also the development of other lower-order dynamic capabilities and the enhancement of new learning routines and practices, which can be used as a learning tool for future technology adoption (Karimi and Walter, 2015; Schuchmann and Seufert, 2015).

Although hypothesis 2 was not supported, the study finds the collective positive impact of DMI, MSI, and SI of factory managers on the breadth of I4.0 technologies to be similar to the concept of integration intelligence. The latter represents the extent to which tactical information technologies are harmonised into a unified system, such as an Enterprise Resource Planning (ERP) system (Heim and Peng, 2010). Such Integration intelligence of factory managers encompasses a gamut of practices, encompassing product design, procurement, shop floor operations, and logistics (Ross and Weill, 2005). The benefits of DMI, MSI, and SI for factory managers on the breadth of I4.0 technologies have been shown to reduce complexity, introduce discretionary work practices (routine changing routines), and shifts in technology focus to foster greater flexibility and the customisation of production equipment of the factory (Ross and Weill, 2005; Heim and Peng, 2010; Bharadwaj et al, 2013; Gerow, Thatcher, and Grover, 2015; Pech and Vrchota, 2022).

The results of this study extend the ongoing discussion on the role of higher-order capabilities, such as design-manufacturing integration (DMI) and systems integration (SI), as key antecedents of first-order capability to adopt and use the breadth of I4.0 factory technology. In this vein, the subsections below highlight the finer details and the contribution of such integration capability related to DMI (section 6.2.1), MSI (section 6.2.2), and SI (section 6.2.3). These subsections discuss in more detail the often-hidden implications and paradoxes of using integration mechanisms, at the level of the factory, to develop the capability to adopt and use the breadth of I4.0 technologies.

### *6.2.1 The link between design-manufacturing integration & breadth of I4.0 technologies*

The findings of this study underscore a significant and positive relationship between the Design-Manufacturing Integration (DMI) capability of factory managers and the capability to adopt and use the breadth of I4.0 technologies ($\beta = .31$, $p < .001$). This positive and significant association aligns with the existing literature, which increasingly emphasises the pivotal role of integrating the design and manufacturing functions (Yang et al, 2018; Xu, Xu and Li, 2018). The previous section of this chapter explained the important contribution of this study in relation to DMI, characterised as a second-order capability at the factory level and found DMI to be an antecedent to the breadth of I4.0 technologies at the factory. This subsection adds to how DMI in particular is positively related to the breadth of I4.0 technologies and how the acceptance of the first hypothesis is theoretically justified.

The theoretical justification for design-manufacturing integration capability positively relating to the breadth of I4.0 technologies is grounded in the realignment of existing design and manufacturing assets for competitive advantage. We have shown that in markets experiencing constant product innovation, factory managers strong in DMI capability can better respond to these market changes as they have more control over the two functions of design and manufacturing. The integration of design and manufacturing functions is demonstrated to enable the seamless exchange of data and information throughout the product lifecycle, a key tenet for staying competitive while adopting I4.0 technologies (Apiliogullari, 2022; Pozzi, Rossi and Secchi, 2023).

This integration capability is found to foster real-time collaboration, automation, and improved decision-making, thereby facilitating the factory managers' capability to adopt and use the breadth of I4.0 technologies (Rivard, Raymond and Verreault, 2017; Doe et al, 2020). In this study, the use of IoT for increasing collaboration among divisions and departments beyond production is noteworthy (Fukuzawa et al, 2022). It is argued that IoT technology benefits uniquely from DMI capability. Bridging I4.0 ICT and production technologies across departments, in this case design and production, requires adequate understanding of the digital maturity of technology and the available resources within each department (Chirumalla, 2021).

At a finer level of detail, the study shows that factory managers who can align product design teams with manufacturing teams and find new ways to coordinate issues are best suited to adopt and use the breadth of I4.0 technologies. By breaking down traditional silos and enabling a holistic view of the production process, DMI is found to create an environment conducive to the broader implementation of hardware and software (Hunde and Woldeyohannes, 2022; Teece, 2022). One salient aspect that resonates with these findings is the literature's recognition of higher-order capabilities like DMI providing the foundational infrastructure and knowledge base required to fully leverage and implement ordinary capabilities like adopting I4.0 technologies. In essence, the DMI capability of factory managers is found to serve as a set of practices and routines aimed at informing design teams about the intricacies of actually manufacturing the designed products in practice.

Mechanisms include using design-for-manufacture/assembly (DFMA) methods and involving manufacturing in NPD projects and for product signoffs to avoid tensions between the two teams during the digital transformation. More complex products have been found to benefit more from such DMI practices in developing the capability to adopt and use the breadth of I4.0 technologies. In this vein, such a relationship suggests that managers of OEM's and high-tech manufacturing sectors with more complex products view DMI as a prerequisite using complex sets of I4.0 technologies. This is justified by the fact that integration capability is often needed for more complex manufacturing processes (Thome and Sousa, 2016). In this context, we find that DMI capability serves as the linchpin that aligns these advanced I4.0 technologies and systems with existing processes and functions (Chiarini, Belvedere and Grando, 2020).

In the context of adopting and using a diverse breadth of I4.0 technologies, the process complexities and differences in technology requirements is mitigated by DMI capability. Similar to the findings of Thome and Sousa (2016), this study finds that certain DMI mechanisms, such as job rotation between the design and manufacturing engineering team, do not necessarily support the breadth of I4.0 technologies at the factory. This is because job rotation is harder to turn into a routine, which may only result in temporary efficiency gains and does not prove advantageous to factory managers' capability to adopt and use the breadth of I4.0 technologies. Nonetheless, this study finds that most DMI practices bridge data, design, and production resources across departments and finds that DMI is instrumental in facilitating the orchestration of disparate I4.0 technologies at the factory (Heim and Peng, 2010; Choi and Kang, 2018; Kamble et al, 2020).

Ultimately, the findings of this study reaffirm the relationship between the cross-functional higher-order capabilities of DMI and the implementation of ordinary capabilities like adopting and using I4.0 technologies at the factory. Several finer contributions are shown in this study. These findings add to I4.0 studies linking the product and production, specifically showing that in the context of DC *"the product is not just processed (acted upon) by the production resources but also controls (interacts with) the production resources"* (Stark et al, 2023). Also, it is evident from the results that factory managers with adequate DMI capability can strengthen their capability to orchestrate bundles of I4.0 ICT and production technologies best understood by teams of design and production departments. Therefore, by fostering DMI capability, factory managers not only leverage the implementation knowledge of various cross-departmental teams but also strengthen their foundations for the digital transformation and position themselves for sustained competitiveness.

### *6.2.2 The link between manufacturing-strategy integration & breadth of I4.0 technologies*

The initial hypothesis posited that Manufacturing Strategy Integration (MSI) would be positively associated with the breadth of I4.0 technologies at the factory. However, after a comprehensive analysis of the survey data, it became evident that there is a weak yet nonsignificant link between MSI and the capability to adopt and use the breadth of I4.0 technologies ($\beta = .03$, $p > .05$). Contrary to prior research on MSI, this study found that factory managers' capability to integrate business strategy with manufacturing strategy does not impact on the capability to adopt and use the breadth of I4.0 technologies. Interestingly, this does not mean that MSI is not valuable as a I4.0 strategy. For instance, MSI could benefit I4.0 depth and source as opposed to the often-specialised breadth (i.e., combination) of production technologies that top management at the strategy level may not fully comprehend the need for.

This lack of a significant relationship can be explained from the DC perspective. In this context, implementing production technologies is shown as part of seizing competitive advantage opportunities by improving the factory manager's ability to identify and understand emerging opportunities and threats. In the case of I4.0, factories need to seize the potential benefits of these technologies, such as increased efficiency, reduced costs, and improved quality. However, the perceived benefits of I4.0 can vary widely depending on contingencies, like the level of existing technology infrastructure, workforce capabilities, and market demands (Braun et al, 2020). If a factory does not perceive significant benefits from I4.0 or faces obstacles in integrating these technologies, managers may prioritise other investments over I4.0. Moreover, investment in I4.0 technologies requires significant financial resources, technological expertise, and organisational changes (Zhang et al, 2021). If a factory lacks the necessary resources or the capability to implement I4.0 effectively, it may choose not to invest in these technologies despite strategic integration efforts that may be undertaken for other purposes.

One key perspective that emerges from this study is that even factories with a well-integrated manufacturing strategy might not have the necessary resources to invest in expensive I4.0 technology, especially with compatibility and other factors in mind (Cagliano et al, 2016). The results indicate that while cross-departmental communication and alignment are known to streamline processes such as just-in-time implementation (Xu and Chen, 2018), this does not necessarily translate into a direct relationship with the adoption and usage of different I4.0 technologies. In this sense, the agility, lean practices, and flexibility cultivated by MSI do not automatically lead to factory managers' capability to adopt and use the breadth of I4.0 technologies. These finer details of this study show that the capabilities needed to adopt sets of advanced production technology extend beyond the realm of traditional manufacturing strategy integration capabilities.

This lack of significance can be explained by competitive strategy as opposed to corporate strategy playing a pivotal role in shaping manufacturing strategy (Ward and Duray, 2000). This implies that the adoption and use of the breadth of I4.0 technologies is predominantly driven by the competitive priorities of the factory and not vice versa. In other words, the strategic manufacturing goals and objectives may be communicated to the factory floor but decisions are not driven or in many cases aligned with corporate strategy. In essence, MSI alone may not be the primary driver of adopting and using the breadth of factory I4.0 technologies. Instead, it is probably influenced by a broader strategic context that aligns factory capability, technology investments, and competitive priorities and country/region-specific contingencies (Wamba et al, 2017; Singhal, 2020; Pessot et al, 2021). Also, managers may experience risk-averse behaviour when it comes to adopting new technology if they are not in full control of the digital transformation. One explanation for this is the uncertainty associated with radical innovation, including potential technological disruptions and the need for retraining the workforce and resistance to change, which can deter decision-makers from developing the capability to adopt and use a broader set of advanced production technologies despite strong MSI (Teece, 1986; Bourlakis et al, 2013; Sweeney et al, 2016; Neely et al, 2019).

While MSI was demonstrated to be non-significant in relation to the capability to adopt and use the breadth of I4.0 technologies, other technologies benefit more greatly from this higher-order capability. Specifically, *"cross-boundary digital technologies"* such as IoT and cloud best align disconnected functions, such as manufacturing and strategy (Bharadwaj et al, 2013; Li, Wang and Hou, 2017; Pech and Vrchota, 2022). This is because the capability of *"pooling knowledge and competence"* across the strategy and production functions, as opposed to corporate management dictating decisions, enables comparison to industry standards and it can provide factory managers with a greater flexibility and responsiveness to modify production systems in response to market changes (Di Maria, De Marchi and Galeazzo, 2022; Teece, 2022).

Another explanation for the nonsignificant link between MSI and the capability to adopt and use the breadth of I4.0 technologies is that factories may not aim to implement I4.0 or avoid implementing too many I4.0 if strategic priorities are focused predominantly on maintaining current capability and performance. Technological path dependence suggests that previous technological choices and investments can significantly influence future decisions (Arthur, 1989; Greve and Seidel, 2015; Sydow, Schreyögg and Koch, 2020; Grodal, Krabbe and Chang-Zunino, 2023). This suggests that at the factory the capability to adopt and use the breadth of I4.0 technologies is developed gradually and over time to allow a broader set of technologies to be adopted and used. On the other hand, factories that have already invested heavily in specific technologies or may depend on legacy machinery may find it challenging to switch to entirely new and more advanced production technologies due to the sunk costs associated with their existing infrastructure. This is because factories develop capabilities, practices and routines around their existing technologies (Levinthal and March, 1993; Zollo and Winter, 2002). This explains the nonsignificant link between MSI and the capability to adopt and use the breadth of I4.0 technologies, as even if the MSI capability of factory managers is strong, the factory may not be able to use some I4.0 technology. This potentially limits the breadth of I4.0 technologies for the factory below what is needed to stay competitive in dynamic markets.

The findings of this study reveal that MSI is not significantly related to the capability to adopt and use the breadth of I4.0 technologies, rejecting the second hypothesis. This unexpected outcome underscores the complexity of technology adoption and the multifaceted nature of the relationship between strategy and advanced technology deployment. While MSI certainly plays a role in shaping manufacturing practices, it is found not to be the sole determinant of the breadth of I4.0 technologies. As factories continue to navigate the evolving landscape of I4.0, a comprehensive understanding of these multifaceted dynamics and specifically strategy related second-order capabilities will be crucial in shaping successful technology adoption (Rodríguez-Espíndola et al, 2022; Marcinkevicius and Vilkas, 2023).

### *6.2.3 The link between systems integration & breadth of I4.0 technologies*

The result of this study shows a positive and significant link between systems integration (SI) and the capability to adopt and use the breadth of I4.0 technologies at the factory ($\beta = .17$, $p < .01$), confirming the third hypothesis. This study contributes to systems integration literature by recognising this higher-order capability as a principal driver of digital transformation to augment communication and knowledge dissemination across diverse subunits. For instance, across the departments of a factory and the upstream and downstream systems of value chain partners that the factory is dependent on for operation (Ross and Weill, 2005; Alaranta and Karlheinz, 2012; Gerow, Thatcher and Grover, 2015). Such management of knowledge from diverse sources is demonstrated to benefit the performance of implementing the breadth of I4.0 technologies (Fugate, Stank and Mentzer, 2009).

Dynamic capability theory provides an explanation for the practical link between SI capability and the capability to adopt and use the breadth of I4.0 technologies. In this context, the factory's ability to adapt and thrive in rapidly changing environments is contingent upon its capacity to integrate, reconfigure, and exploit its resources effectively (Teece, 2007; Teece, 2022). Systems integration capability is found to improve the managers' capability to understand the use of I4.0 resources across specific industries and focus on the seamless interconnection of different technologies and data sources within the factory needed to operate the breadth of I4.0 technologies (Chen et al, 2021).

The results indicate that as factories integrate disparate systems of suppliers/vendors and customers, they enhance their ability to collect, process, and leverage data from various sources, enabling them to respond more effectively to market changes and customer demands that require them to use several I4.0 technologies in production. This, in turn, positions factories to exploit emerging technologies and innovation opportunities by combining the factory specific second-order capability of integrating the data from these various sources to adopt and use the breadth of I4.0 technologies. The results reinforce past studies reiterating stronger external integration to enhance collaboration between I4.0 technology providers and users (Frank, Dalenogare, and Ayala, 2019). To this end, the literature explains smart factory systems can be further integrated even beyond the factory walls by using data from active and passive smart products to draw in data and informational resources from the customer. We find that the SI capability and practices fit the core tenets of higher-order dynamic capability and a major enabler for factories to continually adapt, reconfigure, and exploit available technological resources. Specifically, this study demonstrates how the ability to continuously monitor the order status at various factories enables factory managers to quickly adapt to changes in the downstream processes or systems (Bhatt, 2000; Hasselbring, 2000; Barua et al, 2004).

The results of this study add to the findings of past studies providing factory-level support for the positive link between systems integration technology such as IT adoption. The results of this study add to previous factory level studies showing the benefits of combining I4.0 data technologies (such as Banker et al, 2006) by demonstrating that SI leads to the integration of a spectrum of other critical I4.0 technologies, such as horizontal and vertical integration software, IoT, could, simulation and BDA. Unsurprisingly, we find that factory management with a strong capability to integrate such systems is able to better optimise these production assets and more easily implement the breadth of I4.0 technologies at the factory.

Sandberg, Holmström and Lyytinen (2020) argue; *"deepening digitization of components and functions drives complexity by connecting the platform to multiple social and technical settings and producing new interactions and information exchanges".* According to the authors, this complexity is mitigated by digitisation, enabling analog platforms to be increasingly embedded with digital capacity. The results of this study add to the above findings. In effect, we have shown that routine changing routines regarding the internal, upstream, and downstream integration of data and information lessen these complexities for production technology use.

### *6.3 Research Question 2: Does the capability to implement the breadth of I4.0 technology at the factory lead to improved performance and the competitive advantage of the factory?*

This study contributes to the performance and competitive advantage literature on I4.0 at the level of the factory. In this sense, the study finds that the first-order capability of implementing the breadth of I4.0 technologies at the factory is positively related to factory performance, such as schedule attainment performance (SP), environmental sustainability performance

(EP), and the level of automation performance (AP). This demonstrates competitive advantage gains by using a combination of first-order capability, which in isolation does not provide competitive advantage, and second-order integration capability.

Specifically, this study adds empirical evidence on operational performance and competitive advantage gains of implementing the breadth of I4.0 technologies. In this study we have examined I4.0 technologies, such as factory robotics, augmented reality, IoT, BDA, cloud computing, additive manufacturing, simulation technology, integration technology, and energy technologies. Perhaps expectedly, the results did not find that the capability to adopt and use the breadth of these factory I4.0 technologies improve factory production cost performance (CP), showing wider implications for competitive strategy (Cannon and St John, 2004; Belderbos and Sleuwaegen, 2005; Swink, Narasimhan and Wang, 2007).

In addressing the second research question, this study finds that operational performance benefits from the breadth of I4.0 technology. The results add to and expand on previous research findings on organisational performance outcomes of using I4.0 technologies (Dalenogare, Benitez, Ayala and Frank, 2018; Büchi, Cugno and Castagnoli, 2020; Fatorachian and Kazemi, 2021). The findings of this study contribute to the above performance studies by empirically showing that dynamic capability at the level of the factory is positively related to factory operational performance. These findings reinforce previous DC research identifying capabilities akin to the breadth of I4.0 technologies, such as *"orchestration of digital resources"* and *"creation of novel digital resources",* driving the use of these resources (Piccoli, Rodriguez and Grover, 2022). More specifically, the results add to ongoing discussion characterising dynamic capabilities as a tool for digital technology use and competitive advantage (as in the case of: Li et al, 2022b; Felsberger et al, 2022; Lu, Zhao and Liu, 2022; Sulistyo and Ayuni, 2023; Rehman and Jajja, 2023).

Interestingly, the results of this study found that the factory managers' capability to adopt and use the breadth of I4.0 technologies has a mixed yet somewhat expected impact on factory operational performance. Specifically, the breadth of I4.0 is positively and significantly related to the level of automation, environmental factory emissions, and schedule attainment. Perhaps unsurprisingly, financial measures of operational performance such as production costs are not supported by the breadth of I4.0 technologies, rejecting hypothesis 5. This can be explained by similar studies showing a delayed or lagging manifestation of improved performance. For instance, performance gains have been shown to lag in the case of growing

IT investments (Schweikl and Obermaier, 2020). In this context, we show the difficulties of maintaining and controlling the cost of production for factories focusing on too many complex I4.0 technologies.

Sustained competitive advantage was previously only studied at the level of the factory, showing that supply chain integrative capabilities improve operational performance based on the anticipation of new technology and collectivism (Beheregarai Finger, Flynn and Laureanos Paiva, 2014; Arellano Rebolledo and Tao, 2019; Durach and Wiengarten, 2020). In this study we specifically show that the combination of the first-order capability of using and adopting the breadth of I4.0 technologies supported by second-order capability for both internal and external integration provide competitive advantage, which can be continuously improved and sustained in a turbulent market. This contributes factory level evidence on adopting and using diverse sets of production and ICT I4.0 technologies for operational performance. Thus far studies only focused on other capabilities, such as lean practices (Onofrei et al, 2019; Buer et al, 2021), sustainability practices (Ahmadi-Gh and Bello-Pintado, 2022) and workers' well-being practices (Bellingan et al, 2023).

Another contribution that stands out from this study is that factory managers and smart factory decision-makers need to prioritise the expected outcome of initiating I4.0 projects and using a breadth I4.0 technologies. We show that a breadth of I4.0 technologies improves operational performance and that factory managers often need to make trade-offs (Deflorin and Scherrer-Rathje, 2013). In this sense, we have shown that factory performance improves given an appropriate level of capabilities, yet it is always representative of what is measured at the factory sub-unit level. For instance, lower emissions could be due to carbon credit purchasing and transforming some waste into less regulated waste forms, which could be misleading for regulators and consumers. The results demonstrate that the benefits of I4.0 are numerous and the purpose of implementing broad sets of I4.0 technologies should be considered carefully beforehand, based on the specific short-term and long-term priorities of the factory (Duman and Akdemir, 2021; Angelopoulos et al, 2023). Factories will also find it difficult to focus on broadening technological investment and operational change simultaneously.

The sections below show the finer contributions of this study regarding the impact of the capability to adopt and use the breadth of I4.0 technologies on factory performances. We demonstrate, with the exception of production costs (section 6.3.2), the sustained competitive advantage gained from the level of automation performance (section 6.3.1), factory environmental sustainability (section 6.3.3), and schedule attainment (section 6.3.4). The findings ultimately inform competition strategy based on available mechanisms and capabilities often witnessed, yet still infrequently measured, in technology-focused organisations such as factory-subunits in competitive markets (Petit and Teece, 2021; Teece, 2023).

### *6.3.1 The link between the breadth of I4.0 and level of automation*

The empirical analysis of this study has yielded compelling evidence in support of the fourth hypothesis (H4), which posited a positive relationship between the breadth of I4.0 technologies and the level of factory automation ($\beta = .57$, $p < .001$). This positive relationship shows the benefit of being able to adopt and use a breadth of I4.0 technologies as opposed to isolated adoption. Such findings demonstrate that bundles of technology, when enabled by fundamental capabilities, contribute significantly to the successful automation of tasks (Martell et al, 2023). In this vein, the capability of factory managers to adopt and use the breadth of I4.0 technologies encompasses both manufacturing and information and communication technology, shown to be a catalyst for heightened automation (Oesterreich and Teuteberg, 2016; Frank, Dalenogare and Ayala, 2019). Such a finding also aligns with and adds to the broader literature on the transformative impact of I4.0 technologies on manufacturing processes and the subsequent enhancements in automation (Thoben et al, 2017; Lu, Xu and Wang, 2020; Morgan et al, 2021).

The results provide empirical evidence on the relation between I4.0 and the actual level of automation regarding the various dominant processes of a factory, such as tool change, job setup, product processing, monitoring, inspection, and the movement of material throughout the factory floor. This fills a major gap of providing factory level data on automation, as opposed to previous research, which has only underscored the pivotal role of digitalisation, including broad I4.0 technology adoption in driving automation for manufacturing (Dalenogare et al, 2018; Obermayer, Csizmadia and Hargitai, 2022; Spring, Faulconbridge and Sarwar, 2022; van Dyck et al, 2023).

Perhaps expectedly we find that the adoption of a breadth of I4.0 technologies for factory operations has ushered in a paradigm shift, enabling machines and systems to become more autonomous and self-sustaining (Jayasekara et al, 2022). These advancements of using the breadth of I4.0 technologies provide a constant stream of reliable production data and minimal packet losses, and they underscore the transformative power of I4.0 in automation improvement. This ensures high accuracy and precision, while minimising automation error in the growing automation of inspection and monitoring processes (Syed et al, 2020; Munirathinam, 2020; Leng et al, 2021; Zheng et al, 2021; Psarommatis and Kiritsis, 2022).

This study contributes to the I4.0 automation literature by showing that factories that have adopted several I4.0 technologies particularly enhance automation, as shown by the higher adjusted $R^2$ (0.344) and F value (16.236) compared to the other performances (see table 22). These results demonstrate how adequate adaptation and usage of the breadth of I4.0 technologies plays a more important role in automation, which was once a complementary aspect to manufacturing. Process automation is shown by this study to be intrinsic to the fabric of contemporary manufacturing processes (Mangat, Mangler and Rinderle-Ma, 2021; Hughes et al, 2022).

The findings corroborate recent research that highlights the potential of I4.0 in facilitating resource allocation for production control (Dotoli et al, 2017; Zhang et al, 2021). In this study we have expanded this view and measured factory resources, such as various types of factory manager capabilities and the multitude of factory I4.0 technologies they have access to. Moreover, the importance of data extraction, which is fundamental to automation solutions, has been reaffirmed in this study (Szalavetz, 2019; Xu et al, 2020). This, however, raises issues related to data security and privacy, which is found to limit the extent of automation in certain industries, which could jeopardise their competitive advantage (Rejeb et al, 2020).

Interestingly, the finer results indicate that widespread adoption of I4.0 technologies and the simultaneous deployment of such advanced manufacturing technologies within the factory does not necessarily result in a higher level of automation at the factory (Lee et al, 2019). This can be explained by the traditional perspective of operations management, often portraying automation as potentially reducing flexibility (Yu and Schweisfurth, 2020). In practice, this could diminish the appetite of factory managers to further automate tasks and processes. In this regard, the wider literature indicates that the negative implications of automation can be mitigated using capabilities such as lean production and ensuring an appropriate technology mix (Tortorella et al, 2021; Rossini et al, 2022).

By developing higher-order capabilities, such as integration and alignment practices, automation becomes a means to enhance decision-making and better use the full breadth of I4.0 technologies available in that sector (Salovaara et al, 2019; Goh et al, 2020). Such dynamic capabilities of integrating multiple I4.0 technologies can mitigate operational bottlenecks as well as difficulties in managing and maintaining these complex automation systems (Schuh et al, 2017).

In summary, this study's findings underscore the substantial impact of the factory managers' capability to adopt and use the breadth of I4.0 technologies on the level of factory automation. Ultimately, the findings complement the lack of empirical evidence on this matter and expand on the benefits of I4.0 ICT and production technology for expanding and optimising process and service automation, ultimately boosting competitive advantage (Romero-Silva and Hernández-López, 2020; Wirtz, Kunz and Paluch, 2021).

### *6.3.2 The link between the breadth of I4.0 and production cost*

Hypothesis (H5) initially posited a positive relationship between the factory manager capability to adopt and use the breadth of I4.0 technologies and lower factory production costs. However, the analysis of the data revealed unexpected results, indicating insufficient evidence to reject the null hypothesis. Therefore, there is inconclusive data to suggest that the breadth of I4.0 technologies reduces production costs ($\beta = .10$, $p > .05$). In fact, the results suggest that in some scenarios, higher breadth of I4.0 technology deployed at the factory may in fact be associated with increased production costs. These findings challenge prevailing assumptions that I4.0 technology necessarily reduces the cost of manufacturing, and they underscore the complexity of the relationship between I4.0 technologies and the economics of the digital transformation.

There are several theoretical explanations for the nonsignificant relationship of the breadth of I4.0 technologies to production costs. For instance, it is evident that smaller factories and SME's who have to meet supply chain commitments despite shortages of resources, such as skilled personnel, can incur significant production costs (Mhlongo, 2023). In this sense, when the skill level of the workforce is poor and resources are scarce, operational efficiency suffers and the factory will only be partially cost effective. This condition is found to worsen if the supplier (i.e., resource providers or I4.0 technology vendors) is in competition with the factory using and, in some cases, depending on those I4.0 technologies to keep the cost of production competitive (Lim and Tan, 2010). Conversely, the larger, more resourceful factories, referred to as lighthouses in some industry and policy reports (Gregolinska et al, 2022; WEF, 2023), can more easily absorb a skilled workforce and other resources away from medium and small factories growing and diversifying their I4.0 technology base (Ricci, Battaglia and Neirotti, 2021).

One crucial factor contributing to this unexpected outcome is the substantial initial investment required for a comprehensive adoption of multiple I4.0 technologies and the depletion of resources. Studies have highlighted the potential cost benefits of I4.0 technologies in the context of digitisation (Shukor and Axinte, 2008; Ralston and Blackhurst, 2020), automated inspection systems (Prieto et al, 2002), and 3D printing (Baumers et al, 2016). These results conflict with the findings of this study, showing that bundles of I4.0 technologies incur unexpected overheads and inventory costs. This indicates that the cost-effectiveness of these technologies can vary widely depending on how these technologies are adopted and used by management (Costabile et al, 2017). For instance, it has been shown that the adoption of additive manufacturing, despite its touted advantages, does not always result in lower production costs compared to traditional methods like injection moulding (Pozzi, Rossi and Secchi, 2023).

Another explanation for this nonsignificant link between the factory managers' capability to adopt and use the breadth of I4.0 technologies and production costs is complexity. Arguably, the adoption of bundles of I4.0 technologies is found to add complexity into production processes (Biswas et al, 2020). In this study we specifically show that interconnected systems, machinery, and data streams require additional resource planning, including specialised personnel, maintenance, and infrastructure, to manage and support these technologies effectively in a way that controls overhead costs and is able to make products that can compete with the competition on cost.

The findings hint production costs to sometimes increase as resources are not always readily available or are not properly used by management to address these demands. For instance, the wider deployment of I4.0 technologies increases the need for maintenance and support services, which can add to the cost of the product (Biswas et al, 2020). In addition, Kowalski et al. (2020) found that the complexity of managing and maintaining a wide array of interconnected I4.0 devices and systems can result in increased operational expenses, particularly in terms of ensuring cybersecurity and IT infrastructure upkeep. These results further support the notion that the maintenance of the breadth of I4.0 technologies requires regular software updates, and the troubleshooting of compatibility issues among different systems and components (Singhal and Singhal, 2002; Senna et al, 2022; Dieste et al, 2023).

The results point to the interesting yet often forgotten detail that while I4.0 technologies have the potential to optimise energy use at the factory, their impact on energy-related production costs varies (Rajput and Singh, 2021; Chai et al, 2021; Favi et al, 2022). In some cases, the pursuit of cleaner energy sources, an important facet of I4.0 adoption, may not necessarily translate into direct cost savings as the price of renewable sources of energy may be even higher (Song et al, 2022).

In this context, the results of this study further shed light on the often unpredictable and volatile energy costs as a component of the nonsignificant relation between the breadth of I4.0 and factory production costs. The findings demonstrate that energy consumption issues are inherent to operating multiple I4.0 technologies in tandem. The results fall in line and concur with research on the energy consumption of many I4.0 technologies leading to significant production expenses in certain industries (Liu and De Giovanni, 2019; Chiarini, Belvedere and Grando, 2020; Dieste et al, 2023). The findings of this study offer valuable contributions to the above literature by providing empirical evidence on the breadth of I4.0 technologies at the factory, illustrating the need for a constant stream of supplementary resources (energy, upkeep, integration efforts etc.) to operate these diversified technology bundles cost-effectively. As expected, this is found to be less the case if energy technologies are included in the breadth of I4.0 technologies at the factory, pointing to careful selection of these I4.0 technology bundles. Moreover, we find that I4.0 ICT technologies related to external integration with customers and suppliers do not always result in direct cost reduction, particularly if systems integration capability is underdeveloped (Fabbe-Costes and Jahre, 2008; Wong, Boon-Itt and Wong, 2011; Blome, Schoenherr and Kaesser, 2013; Lorenz et al, 2020).

The findings contribute to the ongoing discourse on the economic impact of I4.0 by shedding light on the intricate dynamics that influence the production costs performance (CP) of the smart factory. Our research results challenge the conventional wisdom that the breadth of I4.0 technologies fundamentally lead to lower factory production costs. Instead, the findings of this study reinforce the notion that *"I4.0 shifts competition from lower cost to higher capabilities"* (Dieste et al, 2023). Ultimately, while this hypothesis was not supported by our data, it underscores the need for better understanding of the multifaceted relationship between the many I4.0 technologies. In this study we have considered bundles of up to nine I4.0 technologies for factories with different sizes and production strategies. It is evident that the cost implications of I4.0 technology is contingent on a host of variables.

### *6.3.3 The link between the breadth of I4.0 and environmental sustainability*

The analysis of the results provides strong evidence in support of the sixth hypothesis (H6). The results show a strong and significant correlation between the breadth of I4.0 technologies at the factory and enhanced environmental sustainability, while controlling for factory size and production strategy ($\beta = .39$, $p < .001$). These findings underscore the profound importance of environmental sustainability gains and specifically lowering the rate of factory emissions to benefit from the factory managers' capability to adopt and use the breadth of I4.0 technologies. Although the literature is rich in showing this relationship, scholars less often shift their attention to the factory sub-unit (Javaid et al, 2022; Waters et al, 2022). In this study we specifically show that the breadth of I4.0 technologies, such as bundles of I4.0 ICT and production technology at the level of the factory, reduces the emission of greenhouse gases, wastewater, and solid waste while minimising environmental accidents and the use of toxic materials in production. Specifically, we contribute empirical evidence to the literature proposing that operational performance shares an intrinsic connection with environmental performance (Pagell and Gobeli, 2009; Li, Dai and Cui, 2020; Alsawafi, Lemke and Yang, 2021).

Dynamic capability theory provides a strong explanation for this relationship. The DC of factory managers can configure their resources to align with sustainability objectives and changing environmental regulations and customer demands (Helfat, 2007; Bag, Gupta and Kumar, 2021). It is clear that a broader implementation of I4.0 technologies provides factories with a richer set of resources, including advanced sensors, data analytics tools, and automation systems (Müller et al, 2018; Frank, Dalenogare and Ayala, 2019). These resources can be configured to monitor and optimise energy consumption, waste management, and other environmental factors, contributing to higher EP of factories investing in bundles of I4.0 resources.

It is evident from the above contribution to the literature and the finer aspects of the results that the breadth of I4.0 technologies enables real-time data collection and analysis for typical factory routines such as procurement (Porter and Heppelmann, 2014; AlNuaimi et al, 2021).

Dynamic capabilities are greatly influenced by a factory's capacity to process and utilise (adopt and use) such information efficiently (Teece, 2018). The factory managers' capability to adopt and use the breadth of I4.0 technologies enables managers to gather and analyse environmental data, allowing for proactive decision-making to reduce emissions and improve overall environmental performance and therefore competitive advantage. The dynamic capabilities of factory managers also encompass the ability to learn from experience and adapt routines and processes for greater sustainability (Zollo and Winter, 2002; Palasciano et al, 2016). This is found to foster a culture of continuous improvement through data-driven insights that can provide sustained competitive advantage at the level of the factory (Avella, Fernández and Vázquez, 1999; Finger, Beheregarai Finger, Flynn and Laureanos Paiva, 2014; Javaid et al, 2021; Khan, Idrees and Haider, 2023). Such learning orientation, enhanced by factory managers' routine changing capabilities, enables them to refine the factory's environmental management practices over time, leading to lower waste and use of toxic materials.

One of the foremost points of significance for the breadth of I4.0 technologies at the factory impacting environmental sustainability is the wider expectation for factories using many I4.0 technologies to embrace green manufacturing. It is clear from the results that other than fulfilling regulatory and stakeholder expectations, smart factory managers are increasingly expected to exhibit a robust commitment to environmental responsibility (Lin, Tan, and Geng, 2013; Alkaraan et al, 2023). This expectation is driven by a convergence of several factors, including market demand for eco-friendly production systems, products, and services. In this study, we have shown that the integration of customer and supplier systems, as well as cross-functional alignment, benefits the effect of the breadth of I4.0 technologies on SP. This indicates that customers actively seek out sustainable offerings, while suppliers are inclined to be associated with factories that share their commitment to environmentally sound practices.

Such an alignment of stakeholder interests, albeit at times divergent, has become instrumental in shaping the competitive landscape. We underline the significance of factory managers' capability to adopt and use the breadth of I4.0 technologies to benefit green manufacturing. It is clear from the results that the profound environmental implications of I4.0 adoption extend far beyond the boundaries of individual factories, permeating the entire downstream and upstream ecosystem. In this sense, we reinforce the idea that digital technologies wield substantial influence over supplier selection and the coordination of activities with supply partners (Caiado et al 2021; Belhadiet al, 2022; Sharma et al, 2023). The results of this study also show that cross-functional capabilities empower the synergistic coordination of internal green supply chain management practices with external environmental initiatives, ushering in significant environmental benefits (Zhu, Sarkis, and Lai, 2007; Kouhizadeh and Sarkis, 2018; Singh and El-Kassar, 2019).

The factory managers' capability to adopt and use the breadth of I4.0 technologies is found to facilitate finer control over pollution by transmuting volatile pollutants into secure mediums if needed, thereby diminishing environmental impact (e.g., converting airborne contaminants into solid waste). We point to various I4.0 technologies, including information technologies, lessening the rate of environmental accidents at the factory. These results expand on previous findings that show that information resources, such as ICT bundles of resources, bolster the inspection rates of industrial pipelines, resulting in a substantial reduction in pollution and accidents (Kumar, Vrat and Shankar, 2021). Other technologies, such as ERP, show similar benefits for data-based targeted pollution prevention (Gupta et al, 2020). Yet what stands out from this study is at the level of the implementation of the breadth of I4.0 technologies optimises the processes, curbing fuel consumption such as transportation while preventing waste and emissions the factory (Liu and De Giovanni, 2019). In the breadth of I4.0 technologies measured in this study we do not consider other interesting resources, such as blockchain technology, which the wider literature indicates adds another layer of control by tracking and integrating internal manufacturing processes, thereby curbing greenhouse gas emissions, energy consumption, and wastewater (Umar et al, 2023). In a similar vein, digital twins (DT) can be used to measure the sustainability status and analyse emission and waste data in real-time, enabling proactive decision-making but these were not included in the breadth of the measured I4.0 technologies (Contini et al, 2023).

Another important contribution of this study is that we show some resources part of the breadth of I4.0 technologies to reduce waste. For instance, additive manufacturing, can be used to repair the factories' machinery and potentially factory equipment and tools, prolonging the life of industrial equipment, reducing waste, lowering energy consumption, and avoiding unnecessary transportation of equipment that is fixable inhouse (Rodrigues et al, 2019; Colorado, Velasquez and Monteiro 2020; Kravchenko, Pigosso and McAloone, 2020). Similarly, other I4.0 technology, such as digitally programmable machines and mechanical arms, are shown to optimise cutting and machining processes, minimising raw material waste and energy consumption, while mitigating the need for human involvement in hazardous environments rich in volatile organic compounds inherent in high volume 3D printing job-shops of the factory (Chan et al, 2020; Väisänen et al, 2022; Margherita and Braccini, 2023; Dieste et al, 2023).

### *6.3.4 The link between the breadth of I4.0 and schedule attainment*

The seventh hypothesis proposed that the capability of the factory manager to adopt and use the breadth of I4.0 technologies is positively related to the factory's schedule attainment ($\beta = .19$, $p < .001$). These results contribute valuable insights to the literature on factory level implications for enhanced scheduling performance (SP). We show that factories suffering from schedule instability benefit from the adoption and use of diverse bundles of I4.0 technology resources. Such resource flexibility allows managers to adjust production processes in response to changing demands (Helfat, 2007).

This positive and significant link between the breadth of I4.0 technologies and SP is explained by DC, which posits that factories capable of resource reconfiguration are able to respond more effectively to production disruptions and shifts in customer orders, thus minimizing scheduling delays (Teece, 2009; Teece, 2014). In this vein, we have shown that I4.0 technology enables real-time data collection and analysis, enhancing the factory's information-based decision-making capabilities (Porter and Heppelmann, 2014; Teece, 2018). Factory managers can make more informed and responsive decisions in scheduling and even future production planning if they develop these capabilities in support of implementing the breadth of I4.0 technologies available to the factory.

In this sense we show that the managers' capability to adopt and use the breadth of I4.0 technologies promotes a culture of continuous learning and improvement through data-driven insights (Schneider and Sting, 2020). This aligns with the core tenets of dynamic capabilities, which involve the ability to learn from experience and adapt routines and processes accordingly to avoid past scheduling mistakes, such as predictable seasonal demand changes (Zollo and Winter, 2002). The finer details of the study further reveal that SP is sometimes not impacted by technology. This is because, despite continuous use of I4.0 resources, unforeseen events such as a blockage of world trade chokepoints and other events such as pandemics and political trade wars can choke access to resources (Ortt, Stolwijk and

Punter, 2020; Madhavan et al, 2022; Müller, Hoberg, and Fransoo, 2022). Such disruptions can completely shift the competitive advantage in the markets.

One major contribution of this study lies in demonstrating the reduction of uncertainty and complexity, enabling improved scheduling, due to the capability to adopt and use the breadth of I4.0 technologies. This includes fluctuating customer requirements, variable raw material availability, and unpredictable internal processing times (Mapes, Szwejczewski, and New, 2000). We have shown that the complexity associated with scheduling is compounded by the number of production assets, which in turn depends on the number of products, the number of parts for each product, and the breadth of suppliers and customers (Rossetti et al, 2023).

Specifically, we show that using a mix of complementary I4.0 technologies, such as electronic data interchange (EDI) and enterprise resource planning (ERP) systems, enables manufacturers to predict and mitigate scheduling issues resulting from market unpredictability, product complexity, machine breakdowns, and technological changes (Ahmad and Schroeder, 2001; Molinaro, Danese, Romano, and Swink, 2022). These technologies enhance visibility into the internal factory dynamics as well as the supply chain, enabling swift responses to disruptions and ensuring that production stays on track.

It is apparent from the finer details of the results that certain I4.0 technologies play a more pivotal role in enhancing SP. Radio-Frequency Identification (RFID) and the Internet of Things (IoT) facilitate real-time information exchange, optimisation algorithms, and decentralised decision-making (Li et al, 2023). This allows for agile responses to unexpected events, such as machine breakdowns or shifts in demand, mitigating disruptions and maintaining the production schedule. Machine learning, enabled by I4.0 technology, contributes to data-driven adjustments in sub-schedules, optimizing resource allocation (Shurrab and Jonsson, 2022). Somewhat unexpectedly, we found the promise of real-time data and predictive SP in I4.0 is significant. It can sometimes lead to over-reliance on automated systems, neglecting the need for human intervention and decision-making, which can further disrupt schedules (Liu et al, 2019).

Another valuable contribution of this study is that we demonstrate that planning and decision-making processes are fundamental to SP, and the breadth of I4.0 technologies significantly enhances these aspects. We clarify how manufacturing operations involve intricate planning and many I4.0 technologies, often requiring adjustments to schedules on a frequent basis.

Inadequate usage of ICT in the breadth of I4.0 technologies can result in inconsistent scheduling computations across departments and sub-units, leading to scheduling irregularities (Germain and Lyer, 2006; Lu, Du and Peng, 2022). Such findings highlight the importance of comprehensively implementing I4.0 technology, showing that factory managers benefit from the seamless coordination among internal functions and data from other systems.

Interestingly we find that the accelerated adoption of I4.0 technologies has raised concerns about the potential to disrupt factory schedules, indirectly introducing scheduling instabilities and delays. This is explained by past research indicating that the rapid implementation of I4.0 sometimes outpaces the organisation's ability to manage and adapt to these advanced technologies. We indicated that as factories increasingly incorporate IoT devices and automation, the complexity of coordinating and maintaining these systems can result in unexpected downtime and production interruptions, causing scheduling delays. Our results also resonate with the findings of Perifanis and Kitsios, (2023) who noted that the integration of sophisticated data analytics and artificial intelligence in I4.0 may require substantial time for data training and system fine-tuning, potentially hampering immediate schedule adherence. This is demonstrated by the empirical results of this study, showing that SP is less prioritised as a competitive priority, compared to factory automation for instance, as evident from the relatively lower adjusted $R^2$ (0.148) and F values for this relationship (1.035) (see table 22).

### *6.4 Chapter Conclusion*

This chapter has discussed the results of the hypothesis. It is shown that integration capability is mostly linked with the capability to implement the breadth of I4.0 technologies at the factory. Specifically, the positive link between DMI and SI on the breadth of I4.0 technologies was elaborated. It was also discussed why MSI did not significantly link with the breadth of I4.0 technologies. The second half of the chapter discussed the second research question and elaborated in depth the positive link between the breadth of I4.0 technologies on AP, EP, and SP. The insignificant link between the former and production cost performance was justified based on alternative explanations.

# Chapter 7. Conclusions and Future Research

### *7.1 Chapter Introduction*

This study has examined higher-order integration capabilities as antecedents to the lower-order capability of adopting and using the breadth of I4.0 technologies and competitive advantage gains at the factory level, based on a random sample of UK factory managers. The chapter discusses the theoretical and practical contributions and implications of this survey and highlights future streams of research requiring further exploration by I4.0 scholars based on the limitations and shortcomings of this study.

### *7.2 Thesis Overview*

This is the first study to provide empirical evidence at the level of the factory on the link between second-order integration capability and the first-order capability of implementing the breadth of I4.0 technologies and competitive advantage. Previous studies focused on other general capabilities at the factory level such as internal networking (Shi and Gregory, 1998; Eriksson, Nummela and Saarenketo, 2014) while integration capability was only mentioned in isolated studies. Also, the breadth of I4.0 was not previously studied at the factory level of analysis in relation to the competitive advantage outcomes. Studies at neighbouring units of analysis (mostly the firm level) increasingly suggested that integration capability related to learning and the reconfiguration of existing resources benefits production technology adoption (Schilke, 2014; Thomé and Sousa, 2016; Geleilate, Parente and Talay, 2021). The factory manager's ability to implement the breadth of I4.0 technologies, representing the capability to manage bundles or sets of I4.0 technologies in orchestration, remained unstudied. In addition, a systematic literature review found the I4.0 literature to be atheoretical and lacking in empirical evidence at many levels. In response to these pressing limitations in the I4.0 literature this research investigated these important capabilities as antecedents to lower-order capability of the breadth of I4.0 and competitive advantage (operational performance) at the level of the factory.

Data was collected using an online web-based survey questionnaire with top factory managers of UK factories using I4.0 technology. Due to the methodology and rigorous research design, a high response rate was achieved, and 320 full responses were recorded and analysed using multiple regression and structural equation modelling (SEM). Using the theory of dynamic capability, the results found that higher-order integration capability mostly benefits the first-order capability of adopting and using the breadth of I4.0 technologies (Schilke, 2014; Teece, 2022, Teece, 2023). While design-manufacturing integration and systems integration were shown to be positively and significantly related to the breadth of I4.0 technologies, manufacturing-strategy integration was not found significant in this relationship. In this case, the relationship shows that higher-order factory capability acts as an antecedent to first-order factory capability, while manufacturing-strategy integration was not specifically found to be important for managing the breadth of I4.0, at least not directly, but may benefit other measures of I4.0 adoption (Büchi, Cugno and Castagnoli, 2020; Cugno, Castagnoli and Büchi, 2021). Another important contribution of this study is that the first-order capability of adopting and using the breadth of I4.0 technologies has been found to be positively and significantly related to the level of automation, environmental sustainability, and the scheduled attainment of the factory, showing competitive advantage benefits. The result indicated that the first-order capability of adopting and using the breadth of I4.0 technologies is not significantly related to the production costs of the factory, showing late or delayed manifestation of operational cost performance and the complex trade-off between cost and other competitive priorities of the factory.

This research contributes to the industry 4.0 literature on orchestrating and managing several interconnected technologies. The results of this study identified unique combination of higher-order and lower-order capability. Factory managers strong in such capabilities have been shown to excel at resource orchestration and resource reconfiguration to not only fully realise the holistic benefit gained from using multiple complementary assets but also to protect the value generated by these I4.0 technologies from imitation (Lardo et al, 2020; Nayernia, Bahemia and Papagiannidis, 2022).

### *7.3 Contribution to Theory*

This survey provides several theoretical contributions to the mostly atheoretical I4.0 literature and the mostly firm-level dynamic capability literature, most importantly, the empirical measurement of the scope and extent of technology usage beyond the rather technology-centric measure of technology maturity. The study provided evidence on the capability of the factory manager to implement a breadth of I4.0 technologies. In this case the measured breadth of I4.0 technologies consisted of ten unique technologies (see chapter 4.5).

Second, the results identified transformational integration and alignment capabilities with the characteristics of second-order transformational capabilities. This study is the first to respond to the limitations of the I4.0 literature by testing these higher-order capabilities as antecedents to the capability of managing the breadth of I4.0 technologies. Specifically, design-manufacturing integration, manufacturing-strategy integration, and systems integration are identified as second or higher-capabilities related to new learning routines, routine changing routines, and the transformation of or adding to resources (Schilke, 2014; Danneels 2016; Danneels, 2017).

Third, the results of this study contribute to the DC literature on the competitive advantage of factories (Xiaosong Peng, Schroeder and Shah, 2011; Vanpoucke, Vereecke and Wetzels, 2014). The study provided empirical data on the level of factory automation, production costs, environmental sustainability in the form of emissions and pollutants, and schedule attainment. The results found competitive advantage benefits, except for production costs, for factory managers supporting their mere capability of adopting and using the breadth of I4.0 technologies with transformational integration capabilities.

The results of the survey provide empirical evidence on the above relationship at the level of the factory and address the thus far limited literature on measuring both the capabilities needed for and competitive advantage outcomes of managing I4.0 technology (Felsberger et al, 2022; Rehman and Jajja, 2023). The use of DC theory enabled the researcher to quantify these difficult to measure resources and capabilities. The study provides evidence on how organisational sub-units, such as the factory, develop and adapt their capabilities in response to changes in technology. This adds to the understanding of how factory managers build the capacity to continuously innovate and optimise operations to respond to technological advancements in competitive markets.

### *7.3.1 Integration antecedents to the breadth of I4.0 technologies*

In light of the important contributions noted above, several finer theoretical contributions stand out. Most critically, this study argues for second-order capabilities acting as antecedents to first-order capability instead of the reverse relationship, which some studies theoretically justify. Specifically, the literature shows that over time I4.0 benefits the cross-functional and cross-system integration capability of managers. This is theoretically explained by studies showing that first and second-order capabilities have a two-way symbiotic relationship as opposed to the one-way relationship between second-order DC acting as antecedent to first-order DC, which this study is focused on (Schilke, 2014). In effect, this study provides a theoretical contribution for the more studied impact of second-order DC acting as antecedent to first-order DC. The results show that factory managers have a better grasp of how best to use the breadth of I4.0 technology if they already possess or have recently developed higher-order capabilities and competencies.

These findings expand on recent similar results regarding second-order integration capability as an important antecedent to I4.0 use in manufacturing (Tabim, Ayala and Frank, 2021). The results of this study specifically show that factory managers are adept in systems integration and design-manufacturing integration capability (e.g., using mechanisms to connect and align production with those functions) to be able to develop a more robust capability to adopt and use an ever-increasing spectrum of available I4.0 technology in the market. Perhaps expectedly, such higher-order capability (routine changing routines) considered as part of the wider management literature is still theoretically disconnected from empirical studies on I4.0 (Raj and Jeyaraj, 2022; Pozzi, Rossi and Secchi, 2023). In response to these major literature limitations, the study measures design-manufacturing integration, manufacturing-strategy integration, and systems integration capability as well as ten I4.0 technologies at the factory level used to drive competitive advantage.

The relation between factory integration capability and the capability to implement the breadth of I4.0 technology reinforces the importance of factory planning, maturity models, frameworks, and the preparedness of factory managers to tackle the often-hidden tensions of digital transformation. Such higher-order capabilities need time to develop and must be better understood and developed prior to adoption by factory managers. These tools and mechanisms serve as an essential compass for navigating the complex terrain of digital transformation. Ultimately, we find I4.0 preparation considering different types of first and second-order capabilities offers a structured framework to guide factories in evaluating their current capabilities and to develop and strengthen selected capabilities based on internal and external resource availability (Simetinger and Zhang, 2020).

### *7.3.2 Breadth of I4.0 technologies as antecedent to factory performance*

There are several theoretical implications regarding lower-order capability and factory performance. This study provides theoretical justification for showing the need for performance trade-offs despite resource availability and the use of dynamic capabilities (Mapes, New and Szwejczewski, 1997; Helfat, 2007; Bag, Gupta and Kumar, 2021). A salient facet of the breadth of I4.0 and the positive link with environmental sustainability lies in the ability of factory managers to illuminate the intricate interplay between environmental and economic performance, each discussed individually in the results chapter. This is because many of the consumption and upkeep issues mentioned with regard to the production costs (see section 6.3.2) are also found to negatively affect factory environmental emission rates (Samadhiya et al, 2022). These results are in line with the theoretical justifications of past studies on this matter arguing for the need for a trade-off between these two domains, with environmental improvements potentially hampering economic metrics to some degree (Shultz and Holbrook, 1999).

This study falls short of categorically claiming that there could be a symbiotic relationship between production costs and environmental performance at the factory. However, it is evident that managers have to balance between these two important competitive priorities (Hart, 1995; Klassen and Whybark, 1999; Klassen, 2001). This study hints at other factors that lead to production costs sometimes spiking independently of the environmental performance (EP). In rare cases, the finding reinforces the notion that a coherent sustainability strategy can effectuate waste reduction and pollution mitigation within manufacturing processes without compromising the economic viability of the factory (King and Lenox, 2001).

### *7.3.3 Dynamic capability for smart factory competitive advantage*

We have shown dynamic capability to be a critical component for smart factory readiness for responding to competitive pressures. Development and strengthening of the dynamic capabilities of factory managers is deemed necessary at an early stage of technology adoption. The study indicated that adequate levels and combination of dynamic capability facilitates the development of comprehensive roadmaps to guide factory managers in systematically broadening and deepening the use of production technology (Chatterjee, Grewal and Sambamurthy, 2002; Črešnar et al, 2020; Liebrecht et al, 2021). These findings support proactive I4.0 planning, ensuring that factory resources are allocated effectively to best gain competitive advantage (Wagire, Rathore and Jain, 2020). The results show that integration not only benefits the utilisation of sets of I4.0 technologies but also the development of other lower and higher-order dynamic capabilities and the enhancement of new learning routines and practices that can be used as a continuous learning asset for future technology adoption (Karimi and Walter, 2015; Schuchmann and Seufert, 2015).

### *7.4 Contribution to Practice*

The results of this study guide factory managers, such as operations managers and factory supervisors, when investing in their higher-order integration capabilities as opposed to only focusing on the adoption and use of I4.0 technologies. In fact, the results of the study clearly indicate that the factory manager's capability to implement these technologies is greatly enhanced by having developed over time the capability to integrate the various interdependent technologies, systems, and functions of the manufacturer and, to some degree, that of the value chain partners. The study can also guide factory top management in charge of adopting I4.0 technology in understanding the performance outcome of such change in production technology.

Specifically, factory managers capable of integrating the design and the manufacturing functions (via mechanisms, routines, and practices) can best combine the usage of design technologies (e.g., CAD, simulation modelling, VR), production technologies (e.g., robotics, AGVs, additive manufacturing), and information technologies (e.g., IoT, BDA, cybersecurity, cloud computing). Also, factory managers capable of integrating systems, of upstream and downstream value chain partners, can best combine the usage of the numerous technologies available to factories in the age of I4.0. The findings inform factory managers capable of integrating the strategy and manufacturing functions that they should not expect benefits to their capability in managing bundles of I4.0 technology. Instead, managers also need to consider if the production strategy is driving corporate strategy (bottom-up) or if the corporate strategy is driving production strategy (top-down) and define which is more in line with competitive strategy (Swink, Narasimhan and Wang, 2007). Therefore, managers need to consider a wider range of strategies that impact technology adoption, not just production strategy, corporate strategy, and the integration between them.

Equally important is the result for factory managers concerned with performance. The findings guide managers with the capability to implement the breadth of I4.0 technologies to deliver greater factory performance. The findings guide factory managers in understanding the performance benefit of I4.0 technology bundles, not just for achieving a higher level of automation at the factory but also for reducing pollutants and toxic emissions from the factory by investing in developing their capability to integrate the various interdependent bundles of I4.0 technologies. The results also guide factory managers focusing on lowering the cost of production and other priorities, such as schedule attainment. The findings show that even factory managers who have developed the capability to implement bundles of I4.0 technologies have to prioritise immediate competitive priorities over less pressing issues, such as ensuring the delivery timeliness of products at the cost of not gaining, and in some cases worsening, production cost performance.

### *7.5 Limitations*

The researcher undertook several measures to ensure the validity, reliability and fit of the model with DC theory, according to the steps proposed by Forza (2002) for survey research in operations management. However, some limitations remain that need to be addressed by I4.0 scholars in future research. First, while this study primarily focused on the exploitation of existing capabilities and resources in the adoption and utilisation of I4.0 technologies, future research should delve into the exploration aspect. Exploration involves experimenting with new technologies, processes, and business models to discover new opportunities and drive innovation and efficiency performance. Balancing exploration and exploitation is crucial for sustained competitive advantage. This would provide valuable insights into how factory managers can effectively navigate the trade-offs between exploiting current capabilities and exploring new opportunities to maintain long-term competitiveness and innovation. Future research should explore how factory managers develop the necessary capabilities for I4.0 adoption. This includes examining training programs, organisational learning mechanisms, and the role of leadership in fostering a culture of innovation. Understanding these processes can provide insights into effective strategies for capability development and address the gaps identified in the current study.

Second, the cross-sectional survey method, though beneficial for this study, can have certain disadvantages. For instance, Cross-sectional surveys capture data at a single point in time, making it challenging to establish causality in the context of I4.0 adoption. This study identified the correlation between the variables, but the evidence for causal conclusion is inherently low for cross-sectional designs. Future experimental research methods and longitudinal survey studies are better suited for establishing causal relationships as they can more strongly distinguish the directionality and effect interactions between resources and competitive advantage (McIver and Lengnick-Hall, 2018). To an equal measure, the temporal ambiguity of cross-sectional survey design is not ideal for understanding dynamic processes such as constantly changing performances, which the above alternative methods and time series analysis can overcome (Bryman, 2016). Also, cross-sectional surveys often rely on closed-ended questions (see section 4.5), restricting the depth of analysis. Alternative qualitative methods such as interviews and case studies provide a more conclusive understanding of the complex interaction between resources (Eisenhardt, 1989; Voss, 2010).

Third, it is evident that Industry 4.0 technologies, such as the IoT, additive manufacturing, and robotics, offer substantial competitive advantage potential. Nonetheless, other important I4.0 technology that is critical for factory operations is not included in the breadth of I4.0 technologies of this study. For example, AI, machine learning, blockchains, CPS, digital twins, and edge computing can be added to the breadth of I4.0 technologies of future studies. This does not mean, however, that scholars should only focus on high breadth cases. Future studies could also investigate the complementarity of only a few I4.0 technologies in resource scarce conditions and low-tech sectors, as opposed to the high-tech sector often expected to also have a high breadth of advanced production technology due to more complex manufacturing processes (Cagliano et al, 2019; Jasperneite, Sauter and Wollschlaeger, 2020). Also, in highly customised or intricate manufacturing environments, complete automation and the use of excessive technology may be challenging due to the need for human intervention, creative problem-solving, and intuitive decision-making (Parasuraman, Sheridan and Wickens, 2000; Turner and Garn, 2022).

Fourth, the management literature on capabilities extends far beyond integration. This oversimplification may not be representative of the diverse set of skills factory managers are expected to possess beyond integration, such as leadership and management support, decision-making, communication, and strategic thinking (Mintzberg, 1973; Smith, 2014). Different managerial capabilities are relevant in various contexts and industries and scholars may overlook industry-specific or context-dependent competencies that are crucial for successful factory management (Teece, Pisano and Shuen, 1997). By exclusively examining integration capability, scholars may miss crucial insights into the broader range of management competencies that contribute to the effective use of technology, for instance, the agility and adaptability required to navigate the evolving challenges in the manufacturing sector and other capabilities that are synergetic to integration but are not included in this study (Eisenhardt and Martin, 2000; Hanson et al, 2016).

Fifth, operational performance is a strong representation of competitiveness but not the only measure for competitive advantage. Rather, competitive advantage in the manufacturing sector is a multifaceted and dynamic concept that requires a more holistic approach. For instance, consumers and stakeholders increasingly value sustainability and CSR practices, yet merely examining environmental emission and waste rates may overlook the potential competitive advantage gained through environmentally friendly practices, green supply chain management practices and social responsibility initiatives (Hult and Ketchen, 2001; Porter and Kramer, 2006; Zhu, Sarkis and Lai, 2008). Also, an exclusive focus on static operational metrics may fail to capture the adaptability and agility required to respond to evolving market conditions and industry disruptions (Eisenhardt and Martin, 2000). In the same vein, ignoring factors such as supplier relationships, logistics efficiency, and collaborative networks can provide an incomplete picture of a factory's overall competitiveness (Cohen and Roussel, 2022). Furthermore, competitive advantage goes beyond operational efficiency and includes strategic positioning and customer-centric factors, such as product quality, customization capabilities, and customer service (Porter, 1985; Treacy and Wiersema, 1993; Phan, 2003; Sheth, Jain and Ambika, 2020).

Finally, there are several limitations associated with only including UK manufacturers in the sample. Findings from a survey focused only on the UK manufacturing sector may lack generalisability to a global context. I4.0 implementation and the inherent cultural and regional challenges can vary significantly across different countries due to variations in technological infrastructure, regulatory environments, and industry structures (Lu, 2017). In this vein, relying only on UK data may limit the ability to capture the full spectrum of industry-specific nuances and variations in I4.0 adoption. This limits the understanding of how I4.0 is integrated across international operations (Castagnoli et al, 2022; Luo and Zahra, 2023).

### *7.6 Future Research Avenues*

Given the limitations of this research identified in the previous section, several avenues for future research can be recommended. First, it is evident that the method of the empirical research for studying the different aspects of I4.0 needs to expand beyond cross sectional examination. The operations management, strategy, and information system management literature points to interesting alternative empirical methods that could be used to measure and study the management of I4.0 technology (Flynn et al, 1990; Lyytinen, 1999; Bettis et al, 2014). Future longitudinal survey studies could capture how the breadth of I4.0 changes over time and clarify if factory managers build the capability to implement the breadth of I4.0 technologies over time to include more technologies in the factory. Such studies could clarify how the breadth changes in competitive markets and analyse why factories may use more, or in some cases, a lower number of I4.0 technologies over time. Such a longitudinal approach could also shed light on the depth of I4.0 and clarify how widely these advanced technologies are used in the value chain and how certain technologies proliferate more than others. Similarly, time-based studies could explore the source of I4.0 and determine if factories start to change strategy over time and develop production technology inhouse rather than purchasing from I4.0 solution providers. Future multiple case studies could focus on critical capabilities such as design-manufacturing integration and systems integration, which this study surveyed.

Second, more I4.0 technologies could be added to the breadth of I4.0 measured in future studies. Many important I4.0 technologies, such as blockchain technology and artificial intelligence, were not in the breadth of I4.0 of this study. Including such technologies captures a more representative view of what I4.0 technologies factories have access to in the market (Cugno et al, 2022). Future studies could examine other measures of I4.0 technology usage that would represent the scope and maturity of the technology used, for instance, advanced manufacturing capability (Chung and Swink, 2009), complementary production asset adoption (Christmann, 2000), and advanced manufacturing technology (AMT) used in various areas of the factory such as inventory, job-shops, and assembly lines (Das and Narasimhan, 2001; Das, Narasimhan and Talluri, 2006). Equally, future empirical studies could shed light on digital maturity (Lorenz et al, 2020) and Industry 4.0 maturity as important technology related capabilities measures (Tortorella and Fettermann, 2017).

Third, other capabilities could be measured as antecedents to the breadth of I4.0 technologies. Future studies could clarify if integration capability with other functions could benefit the factory managers' capability to implement the breadth of I4.0 technologies, for instance, integration with marketing (Swink and Song, 2007; Feng, Huang and Avgerinos, 2018), sales (O'Leary-Kelly and Flores, 2002), Human Resources (Santos, 2000), and other aspects of the supply chain (Cagliano, Caniato and Spina, 2006). Beyond integration capabilities, other capabilities identified as second order capability could be studied as antecedents to the breadth of I4.0 technologies. For instance, factory flexibility could be further investigated as a key enabler (Koste, Malhotra and Sharma, 2004). Identifying resourceful and innovative combinations of different types of capabilities could further explain how to best protect I4.0 value in competitive markets (Ellonen, Jantunen and Kuivalainen, 2011; Kuuluvainen, 2012).

Fourth, this study only measured four performance outcomes at the factory level. Future studies could further investigate factory level performance and empirically measure other performance indicators representative of competitive advantage, such as customer satisfaction and customisation responsiveness (Das and Narasimhan, 2001; Bozarth et al, 2009). Another important performance not measured here is quality. Future surveys could fill this gap and measure the delivery quality (Ahmad and Schroeder, 2009), conformance quality (Devaraj, Hollingworth and Schroeder, 2004) and factory level leadership involvement in quality (Xiaosong Peng, Schroeder and Shah, 2011). Equally, future studies could quantify the availability of quality data and reporting methods at the factory level to clarify the availability, timeliness and extent of data on various quality performance measures (Kaynak, 2003).

Lastly, this study only examines the manufacturing sector of the UK. However, I4.0 technologies are also widely used by other industrial and developing countries and for other sectors, such as the service sector. Such studies could clarify the cross-cultural and regional contingencies related to the development of capabilities, technology acceptance, and the ease of adopting new learning routines (Raj et al, 2020; Pessot et al, 2021). Studying the industry level context of implementing I4.0 technologies of factories in developed and developing countries could better explain the inter dependence between plants using I4.0 technologies (Gattiker and Goodhue, 2005). Conversely, future studies could compare implementation cases across different regional and cultural contexts to find similarities and point out the differences in adopting I4.0 technology, such as the developmental culture of the factory and factory culture (Naor, Linderman and Schroeder, 2010; Hardcopf, Liu and Shah, 2021). This would help understand the nuances and variations in I4.0 adoption globally and identify best practices that can be generalised or adapted to different settings. This approach addresses the limitation of the current study's focus on UK factories and enhances the generalisability of the findings. In the same vein, future studies could investigate cultural aspects related to workforce development and learning from failure (Narasimhan et al, 2006; Carmeli, 2007).

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Zhu, Q., & Sarkis, J. (2004). Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises. Journal of Operations Management, 22(3), 265-289.

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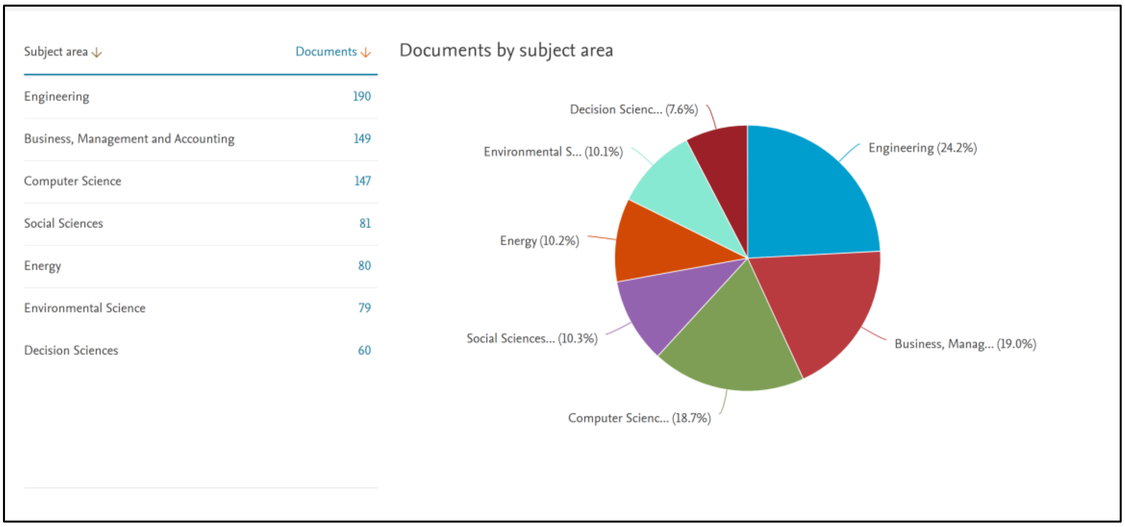
Zollo, M. and Winter, S.G., 2002. Deliberate learning and the evolution of dynamic capabilities. Organization science, 13(3), pp.339-351.

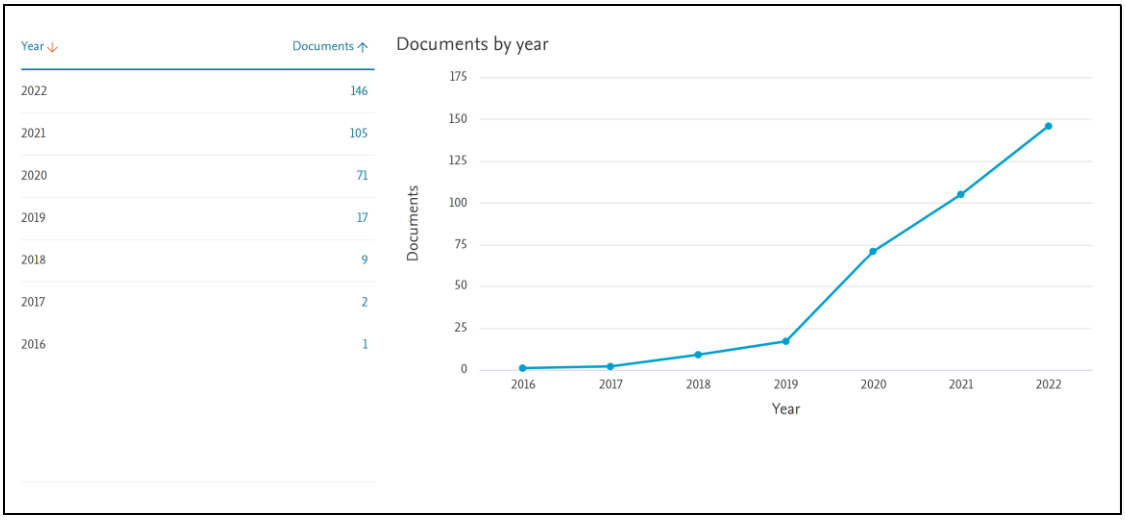
Zonta, T., Da Costa, C. A., da Rosa Righi, R., de Lima, M. J., da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in Industry 4.0: A systematic literature review. Computers & Industrial Engineering, 150, 106889.

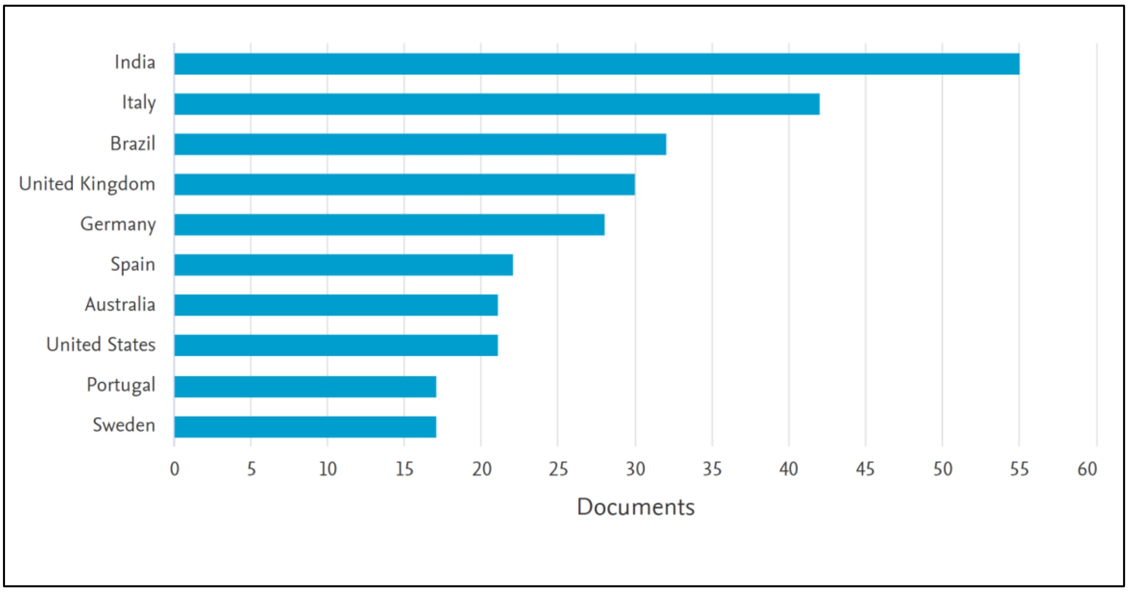
Zott, C., & Amit, R. (2007). Business model design and the performance of entrepreneurial firms. Organization Science, 18(2), 181-199.

# Appendices

## *Appendix A: Scopus I4.0 Search for Review Articles*

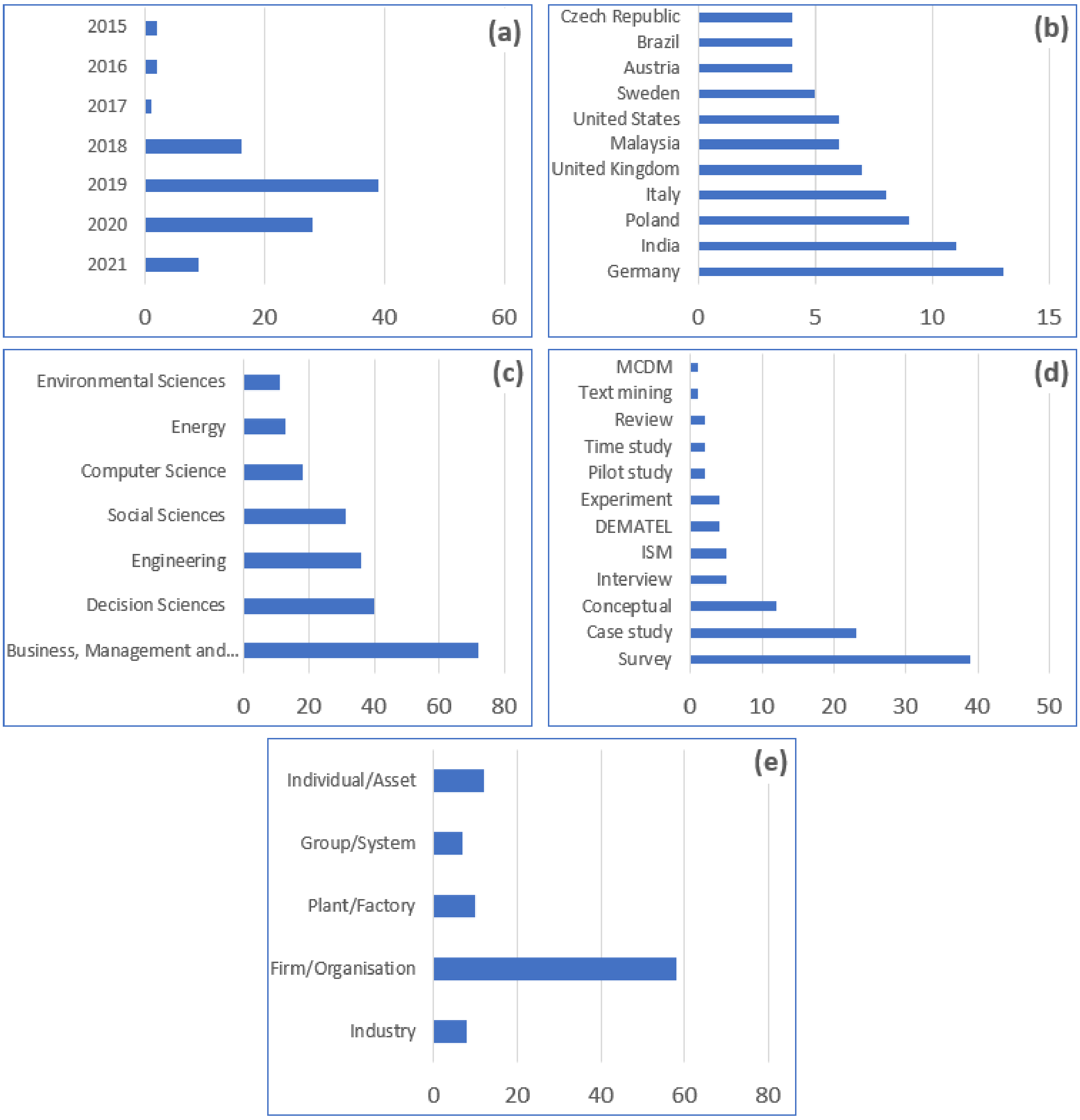


*Appendix B: Selected studies year, origin, field, method, and unit-of-analysis*

publication year (a), country of origin (b), field of science (c), research method used (d), and unit-of-analysis (e)




*Appendix C: Survey checklist based on Forza, (2002)*

| Survey phase | Check questions to assure survey research quality |
|---|---|
| Before Survey<br>Research design | (1) Is the unit of analysis clearly defined for the study?<br>(2) Are the construct operational definitions clearly stated?<br>(3) Are research hypotheses clearly stated? |

| | |
|---|---|
| Defining the sample | (4) Is the sample frame defined and justified?<br>(5) What is the required level of randomness needed for the purposes of the study?<br>(6) What is the minimum sample size required for the planned statistical analyses?<br>(7) Can the sampling procedure be reproduced by other researchers? |
| Developing measurement instruments | (8) Are already-developed (and preferably validated) measures available?<br>(9) Are objective or perceptual questions needed?<br>(10) Is the wording appropriate?<br>(11) In the case of perceptual measures, are all the aspects of the concept equally present as items?<br>(12) Does the instrumentation consistently reflect that unit of analysis?<br>(13) Is the chosen scale compatible with the analyses which will be performed?<br>(14) Can the respondent place the answers easily and reliably in this scale?<br>(15) Is the chosen respondent(s) appropriate for the information sought?<br>(16) Is any form of triangulation used to ensure that the gathered information is not biased by the respondent(s) or by method?<br>(17) Are multi-item measures used (in the case of perceptual questions)?<br>(18) Are the various rules of questionnaire design (see above) followed or not? |
| Collecting data | (19) What is the response rate and is it satisfactory?<br>(20) How much is the response bias? |
| Assessing measure quality | (21) Is face validity assessed?<br>(22) Is field-based measure pre-testing performed?<br>(23) Is reliability assessed?<br>(24) Is construct validity assessed?<br>(25) Are pilot data used for purifying measures or are existing validated measures adapted?<br>(26) Is it possible to use confirmatory methods? |
| Analysing data | (27) Is the statistical test appropriate for the hypothesis being tested?<br>(28) Is the statistical test adequate for the available data?<br>(29) Are the test assumptions satisfied?<br>(30) Do outliers or influencing factors affect results?<br>(31) Is the statistical power sufficient to reduce statistical conclusion error? |
| Interpretation of results | (32) Do the findings have internal validity?<br>(33) Is the inference (both relational and representational) acceptable?<br>(34) For what other populations results could still be valid? |

*Appendix D: Pilot Study Interview Question Example*

## Implementing I4.0 at the plant level

The aim of this interview is to highlight some of the factors that distinguish between I4.0 implementation between different factories.

1. Can you talk to us about the implementation of Industry 4.0 at the firm and then at the plant level? (e.g., Are there differences or similarities?)
2. What is the level of maturity of I4.0 at your company?
3. Is implantation of I4.0 managed at the firm or plant level?
4. What are the critical success factors for implementing I4.0 at the firm and plant level?
5. What are the benefits of I4.0 at the firm level and at the plant level?
6. How much are developed in house? Does your factory collaborate with external partners for the implementation of I4.0 in the factories?
7. How many plants/factories are there in the company, in the base country and internationally?
8. What are the core components of I4.0 at the plant level?
9. What are the main changes that have been made at the firm and plant level to support the implementation of Industry 4.0?
10. Is the level of investment of I4.0 similar across all plants? If not, what are the key factors that differentiate the level of I 4.0 across different plants.
11. What are the plant characteristics that determine low and high levels of investment in I4.0?
12. How important do you find the plants social sustainability as an enabler of I4.0? (Workforce learning and development, supplier/customer relations etc...)
13. How important do you find the plants environmental sustainability as an enabler of I4.0? (Rate of plant emission etc.…)
14. How important do you find the plants openness as an enabler of I4.0? (Working with other plants, departments etc...)

15. How important do you find the plant's product complexity (or production complexity) as an enabler of I4.0? (I4.0 solutions only implemented for complex products?)
16. Other than the above potential enablers and plant size, age, and production strategy, what other factors could enable the implementation of I4.0?

### *Appendix E: Pilot Study Interview Response Example*

| Role/Position | Affiliation/ Field | Interview Response Examples |
|---|---|---|
| Global head of automation, electrical and digital engineering | SPX Flow | Q1: 'We have been able to collect more data and we have been able to contextualise that data'. ('giving the implementors a bigger torch').<br>Q6: 'I buy the equipment [sensors] from the people that make it good, but should I share the data from analysis with e.g., Microsoft?' I want a unique tool that's better than everyone else … because everyone else already has their own tool'.<br>Q13: 'They [companies] are not changing their habit to make their manufacturing process more sustainable' …. 'They buy carbon credits and plant trees'.<br>Q14: 'education and training of the workforce is critical for cyber security'. |
| Global Research Director for Digital Transformation | Global Business Research | Q4: 'decisions are pushed down the line' ... '90% of organisations are doing agile on paper only'.<br>Q6: 'it forces the SMEs into partnership and cooperation' ... 'We used to sell the machines but now we sell services based on that machine'.<br>Q9: 'top management has to understand but also empower employees' … 'depends on change management and culture'.<br>Q12: 'use objective data to measure performance of employees' … ' Need to have the right data in the right form and at the right time to make decisions'.<br>Q16: 'health and safety is important in automation (as an outcome)'. |
| Senior Smart Factory Consultant | Trumpf | Q3: 'manufacturing strategy defines the firm's strategy'.<br>Q4: 'more alignment is needed as this will reduce the cost of the produced parts and products'. |

| | | |
|---|---|---|
| | | Q5:'customers primarily implement digitisation projects to reduce cost of operation'.<br>Q6:'the level of infrastructure of the customer determines the decision to outsource or [invest in] internal R&D'.<br>Q12:'Sustainability and social aspects are very much relevant'.<br>Q14:'perliminary study of the customers digitisation is needed… but to measure the digitisation maturity of customers a benchmarking is done'. 'No general agreement between the firm and digitisation partners (customers) but instead NDA with and based on trust and reputation'.<br>Q15:' Product complexity determines, to a degree, the openness to share data [with suppliers] … SMEs are more affected'. |
| Manager to CEO | Mercedes-Benz | Q4; 'standardised assets form the basis of implementing future Industry 4.0 [technology]'.<br>Q6: 'The full benefit we get when everything is connected in the whole chain either horizontally [and] or vertically'.<br>Q9: different types of PLC's require different systems integration and is going to be much more barrier [difficult]'.<br>Q12; 'the usage of less resources, less energy, less, air and light is embedded in the process of technology implementation'. 'Sustainability is not the primary output'.<br>Q14: 'the end user of the technology is a part of the process of technology development'.<br>Q15:'not as heavily, won't need full system integration or additive manufacturing unit for simple products. |
| Senior Researcher | Innovation and Technology Management (Newcastle University) | Q4:'[enabler] such as lean are fine if you have a very well-functioning supply chain'. 'It's important to the customer to have the things when they want it not that it is only just in-time [Agile]'. 'Factories are dependent on technologies that allow you to maintain a very just-in-time [agile] supply chain'.<br>Q9:'Technology is not easily imposed on people... [which is] often what's going on in practice'.<br>Q12:'workforce-development Is not an intrinsic measure of sustainability'. 'When you |

| | | |
|---|---|---|
| | | have people inputting data into a system… than you have issues of data quality'. Q13: 'a lot of companies use the TBL characterisation of sustainability but trade one dimension against the other'. 'TBL is being abused [misrepresented] being used for greenwashing'. Q14:'power relations between the organisations… the supplier has no choice to invest in the technology [CAD] if they want to stay in businesses. 'The extent to which these [implemented] technologies are adhering to industry wide standards… [which firms] understood in telecommunications…microelectronic design'. Q15: ''for certain products there are some instances where you don't want things to be lean…where engineers [often] over-engineer'. |

*Appendix F: Survey Questionnaire*

# Survey: Smart Factory and Industry 4.0 in the UK Manufacturing Sector

Welcome to this survey that aims to understand the capabilities and practices that would support Industry 4.0 technology use in the manufacturing sector in the UK. This survey is part of an Industry 4.0 (I4.0) and Smart Factory research conducted by Hamed Nayernia (b5053090@newcastle.ac.uk) with the supervision of Dr. Hanna Bahemia and Prof. Savvas Papagiannidis at Newcastle University Business School in the UK.

**You should only proceed to answer this question if your role is Plant Manager/ Plant Supervisor/ Plant Director or Operations Manager/Supervisor.** You will be asked questions related to your factory/plant. When you answer the questions, please refer to ONLY the plant at which you work. Do not consider other plants that your company may operate. If your responsibilities extend beyond a single manufacturing plant, please only refer to ONE plant at which you have a better understanding of its operations.

Some questions may be of a personal nature. However, please be assured that all answers you provide will be kept confidential. Any information provided will be used solely for the purpose of this research. It is very important that you answer all the questions and provide answers that suit your circumstances best. The survey takes 15 minutes to complete. If you do not complete the survey, we will ignore the response and any data provided will not be used in the analysis.

**If you are a manager / supervisor / director at a factory and consent to using your responses as mentioned above, please enter your Prolific ID:**

## XXXXXX

Q1: Degree of I4.0 Technology

Please state if the following I4.0 technologies are adopted and implemented in the plant.

If "Implemented" Please state the origin of the technology. (Either acquired from other companies OR developed in-house).

If the technology was purchased or acquired from another firm, please select "Implemented and acquired from other companies". If in-house innovation and internal R&D led to implementation of the I4.0 technology, in contrast to being purchased from other firms please select "Implemented and developed in-house".

| | It Has Not Been Implemented | Implemented and acquired from other companies | Implemented and Developed Inhouse |
|---|---|---|---|
| a) **Advanced manufacturing solutions**: This refers to the creation of interconnected and modular systems that guarantee automated industrial plans. These technologies include automatic material-moving systems and advanced robotics, the latter of which are now on the market as "Cobots" (collaborative robots) or automated guided vehicles or unmanned aerial vehicles. | | | |
| b) **Augmented reality**: This involves a series of devices that enrich (or lessen) human sensory perception through access to virtual environments; this is accompanied by sensory elements, such as sound, smell, or touch. These elements can be added to mobile devices (smartphones, tablets, or PCs) or other sensors to augment vision (augmented-reality glasses), sound (earphones), or touch (gloves) to provide multimedia information. | | | |
| c) **Internet of Things**: This corresponds to a set of devices and intelligent sensors that facilitate communication between people, products, and machines. | | | |
| d) **Big data analytics**: This relates to the technologies that capture, archive, analyse, and disseminate large quantities of data derived from the products, processes, machines, and people interconnected in a company, as well as the environment around it. | | | |
| e) **Cloud computing**: Cloud computing technologies facilitate the archiving and processing of large quantities of data with high performance in terms of speed, flexibility, and efficiency. Cloud computing also results in a greater number of services developed based on data for a productive system – including monitoring and control functions – to ensure quality and improve operations and production. | | | |
| f) **Cyber security**: This includes security measures designed to protect the flow of information over interconnected corporate systems. | | | |
| g) **Additive manufacturing**: This additive production process allows for complex products by creating layers of materials, including such different types of materials as plastics, ceramics, metals, and resins, thus eliminating the need to assemble the material. A significant example is 3-D printing. | | | |
| h) **Simulation**: This involves reproducing the physical world in virtual models and allowing operators to test and optimize the settings to obtain materials, productive processes (discrete elements), and products (finished or distinct elements). | | | |
| i) **Horizontal and vertical integration**: The integration offered by Industry 4.0 is characterized by two dimensions: internal versus external. The first (horizontal integration) concerns the integration and exchange of information among the different areas in the company. The second (vertical integration) concerns the company's relationships with its suppliers and customers. | | | |
| j) **Other enabling technologies**: These include several technologies used for specific fields, such as tools to determine where, when, and how energy resources are used with the aim of eliminating or reducing waste (Smart grid/energy). | | | |

Q2: Design Manufacturing Integration

When it comes to the integration between the design unit of your company and the manufacturing unit at the plant, please state if you agree with the following statements. (1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree or disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree).

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| a) Our product designers make use of manufacturability guidelines. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| b) We have created new ways to coordinate design/manufacturing issues. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| c) We use design-for-manufacture/assembly (DFMA) methods. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| d) Manufacturing involvement and sign-off is required for new products. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| e) Product designers and manufacturing staff have equal status in NPD projects. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| f) We practise job rotation between design and manufacturing engineering | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Q3: Manufacturing Strategy Integration

When it comes to the integration between the strategy unit of your company and the manufacturing unit at the plant, please state if you agree with the following statements. (1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree or disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree).

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| a) We have clearly defined strategic manufacturing goals and objectives. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| b) Our firm's strategy leverages existing capabilities. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| c) Corporate strategy at our firm drives manufacturing decisions. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| d) Manufacturing strategies and goals are communicated to all employees. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| e) Manufacturing strategy is frequently reviewed and revised. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| f) Manufacturing strategy is well aligned with corporate strategy. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Q4: Systems Integration

When it comes to systems integration and the use of data in your plant, please state if you agree with the following statements. (1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neither agree or disagree, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree).

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| a) Data can be shared easily among various internal systems | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| b) Order changes are automatically reflected in downstream processes or systems | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| c) Our system can easily transmit, integrate and process data from suppliers/vendors and customers | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| d) | Our system shows continuous monitoring of order status at various stages in the process | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| e) | Employees can easily retrieve information from various databases for decision support | | | | | | | |

Q5: Product

What is the main product(s) of your plant?

Q6: Industry

To which industry does your plant belong?

Q7: Factory Age

| | |
|---|---|
| What is the age of the plant? *(Years)* | up to 5<br>6-10<br>11-15<br>16-20<br>21 or more |

Q8: Unionisation

| | |
|---|---|
| Approximately what percentage of plant production workers (if any) are represented by a union(s)? | None<br>1–25%<br>26–50%<br>51–75%<br>76–99%<br>100% |

Q9: Production Strategy

| | |
|---|---|
| What production strategy do you predominantly use at your plant? | Make-to-order (MTO)<br>Make-to-stock (MTS)<br>Assemble-to-order (ATO)<br>Engineer to order (ETO) |

Q10: Factory size

| | |
|---|---|
| How many full-time employees work in your plant? | 1-100<br>101-200<br>201-300<br>301-400<br>401-500<br>501+ |

Q11: Production flexibility (Mix & Volume)

| | |
|---|---|
| How would you describe the primary product mix and volume at your plant? (Please choose one) | High volume and high mix<br>High volume and low mix<br>Low volume and high mix<br>Low volume and low mix |

Q12: Automation

Please rate the level of automation at your plant for the following operations. (1 = None, 2 = Low, 3 = Moderate, 4 = High, 5 = Total).

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| a) | Tool change. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| b) | Job set up. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| c) | Job or product processing. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| d) | Process monitoring | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| e) | Process inspection | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| f) | Material movement | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Q13: Schedule Attainment

Please state if you agree with the following statements on schedule attainment at your plant compared to the industry average. (1 = Strongly disagree, 2 = Disagree, 3 = Neither agree or disagree, 4 = Agree, 5 = Strongly agree).

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| a) | We usually meet the production schedule each day | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| b) | Our daily schedule is completed on time. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| c) | We cannot adhere to our schedule on a daily basis. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| d) | It seems as if we are always behind schedule. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Q14: Environmental Performance

When it comes to environmental performance of the plant, please indicate the extent of the following, compared to industry average (1 = Very poor, 2= Poor, 3 = About the same, 4 = Good, 5 = Excellent).

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| a) | Reduction of air emission. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| b) | Reduction of wastewater. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| c) | Reduction of solid wastes. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| d) | Decrease of consumption for hazardous/harmful/toxic materials. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| e) | Decrease of frequency of environmental accidents. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| f) | Improve the enterprise's environmental situation. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Q15: Production Cost

When it comes to the production cost of the plant, please indicate the extent to which your plant performs the following actions, compared to competition (1 = Strongly disagree, 2 = Disagree, 3 = Neither agree or disagree, 4 = Agree, 5 = Strongly agree).

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| a) | Produces products with low costs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| b) | Produces products with low inventory costs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| c) | Produces products with low overhead costs. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| d) | Offers price as low as or lower than our competitors. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |

Q16: Role

What is your position in the plant?

Q17: Experience

How many years have you worked in this position?

Q18: Education

| | |
|---|---|
| What is your highest degree? | Some high school or less<br>High school graduate or equivalent<br>Vocational/technical school (two-year program)<br>Some college, but no degree<br>College graduate (four-year program)<br>Some graduate school, but no degree<br>Graduate degree (MSc, MBA, PhD, etc.) |

Q19: Thank you very much for your time and effort to complete this survey.

If you have any comment, please type it in the below field:

To receive your funds from Prolific, please take a note of the code below and click next to submit the survey.

XXXXXX

**End of Survey**

*Appendix G: Standard Industrial Classification (SIC) of the Sample*

| SIC Code (Sector) | Frequency (Factory) | Percent (%) |
|---|---|---|
| 10130 | 1 | 0.3 |
| 10612 | 1 | 0.3 |
| 10860 | 28 | 8.8 |
| 10890 | 4 | 1.3 |
| 10920 | 1 | 0.3 |
| 11040 | 1 | 0.3 |
| 13300 | 3 | 0.9 |
| 13923 | 2 | 0.6 |
| 13960 | 1 | 0.3 |
| 13990 | 2 | 0.6 |
| 16290 | 4 | 1.3 |
| 17120 | 4 | 1.3 |
| 17211 | 1 | 0.3 |
| 17220 | 1 | 0.3 |
| 17230 | 3 | 0.9 |
| 18129 | 6 | 1.9 |
| 19201 | 2 | 0.6 |
| 19209 | 1 | 0.3 |
| 20110 | 1 | 0.3 |
| 20130 | 3 | 0.9 |
| 20160 | 3 | 0.9 |
| 20170 | 1 | 0.3 |
| 20301 | 3 | 0.9 |
| 20411 | 3 | 0.9 |
| 20420 | 3 | 0.9 |
| 20590 | 3 | 0.9 |
| 21100 | 13 | 4.1 |
| 21200 | 2 | 0.6 |
| 22110 | 1 | 0.3 |
| 22210 | 2 | 0.6 |
| 22220 | 7 | 2.2 |
| 22290 | 2 | 0.6 |
| 23190 | 1 | 0.3 |
| 23320 | 5 | 1.6 |
| 23430 | 1 | 0.3 |
| 23700 | 1 | 0.3 |
| 23990 | 2 | 0.6 |
| 24100 | 5 | 1.6 |
| 24200 | 11 | 3.4 |
| 24450 | 1 | 0.3 |
| 24520 | 1 | 0.3 |
| 25110 | 4 | 1.3 |
| 25120 | 1 | 0.3 |
| 25210 | 2 | 0.6 |
| 25290 | 1 | 0.3 |
| 25400 | 2 | 0.6 |
| 25500 | 1 | 0.3 |
| 25610 | 1 | 0.3 |
| 25620 | 2 | 0.6 |
| 25940 | 1 | 0.3 |
| 26110 | 14 | 4.4 |
| 26120 | 3 | 0.9 |
| 26200 | 1 | 0.3 |
| 26301 | 1 | 0.3 |
| 26309 | 2 | 0.6 |
| 26400 | 1 | 0.3 |
| 26511 | 6 | 1.9 |
| 26512 | 1 | 0.3 |
| 26513 | 2 | 0.6 |
| 26701 | 1 | 0.3 |
| 27110 | 1 | 0.3 |
| 27120 | 1 | 0.3 |
| 27320 | 3 | 0.9 |
| 27400 | 2 | 0.6 |
| 28110 | 5 | 1.6 |
| 28131 | 2 | 0.6 |
| 28140 | 3 | 0.9 |

| | | |
|---|---|---|
| 28220 | 2 | 0.6 |
| 28250 | 6 | 1.9 |
| 28290 | 3 | 0.9 |
| 28302 | 1 | 0.3 |
| 28410 | 4 | 1.3 |
| 28490 | 1 | 0.3 |
| 28921 | 4 | 1.3 |
| 28923 | 2 | 0.6 |
| 28930 | 3 | 0.9 |
| 28960 | 2 | 0.6 |
| 28990 | 4 | 1.3 |
| 29100 | 31 | 9.7 |
| 29310 | 1 | 0.3 |
| 29320 | 5 | 1.6 |
| 30110 | 6 | 1.9 |
| 30200 | 1 | 0.3 |
| 30300 | 11 | 3.4 |
| 31010 | 4 | 1.3 |
| 31020 | 3 | 0.9 |
| 31090 | 4 | 1.3 |
| 32120 | 1 | 0.3 |
| 32300 | 1 | 0.3 |
| 32500 | 8 | 2.5 |
| 32990 | 5 | 1.6 |
| 33200 | 2 | 0.6 |
| Total Sample | 320 | 100% |

Source: Based on Product/Sector. SIC from: https://resources.companieshouse.gov.uk/sic/

## *Appendix H: Survey Measures*

| Item | Label | Source | Operationalisation |
|---|---|---|---|
| Design-Manufacturing Integration | DMI | Swink and Nair, 2007 | Adopted |
| 1. Our product designers make use of manufacturability guidelines. | DMI-1 | | |
| 2. We have created new ways to coordinate design/manufacturing issues. | DMI-2 | | |
| 3. We use design-for-manufacture/assembly (DFMA) methods. | DMI-3 | | |
| 4. Manufacturing involvement and sign-off is required for new products. | DMI-4 | | |

| Item | Label | Source | Operationalisation |
|---|---|---|---|
| 5. Product designers and manufacturing staff have equal status in NPD projects. | DMI-5 | | |
| 6. We practise job rotation between design and manufacturing engineering | DMI-6 | | |
| Manufacturing-Strategy Integration | MSI | Narasimhan, Swink and Kim, 2006 | Adopted |
| 1. We have clearly defined strategic manufacturing goals and objectives. | MSI-1 | | |
| 2. Our firm's strategy leverages existing capabilities. | MSI-2 | | |
| 3. Corporate strategy at our firm drives manufacturing decisions. | MSI-3 | | |
| 4. Manufacturing strategies and goals are communicated to all employees. | MSI-4 | | |
| 5. Manufacturing strategy is frequently reviewed and revised. | MSI-5 | | |
| 6. Manufacturing strategy is well aligned with corporate strategy. | MSI-6 | | |
| Systems Integration | SI | Barua et al, 2004 | Adapted from firm to factory level |
| 1. Data can be shared easily among various internal systems. | SI-1 | | |
| 2. Order changes are automatically reflected in downstream processes or systems. | SI-2 | | |

| Item | Label | Source | Operationalisation |
|---|---|---|---|
| 3. Our system can easily transmit, integrate and process data from suppliers/vendors and customers. | SI-3 | | |
| 4. Our system shows continuous monitoring of order status at various stages in the process. | SI-4 | | |
| 5. Employees can easily retrieve information from various databases for decision support. | SI-5 | | |
| Breadth of Industry 4.0 technologies | I4.0B | Büchi, Cugno and Castagnoli, 2020 | Adopted |
| 1. Advanced manufacturing Solutions (e.g., Robots) | I4.0B-1 | | |
| 2. Augmented reality | I4.0B-2 | | |
| 3. Internet of Things | I4.0B-3 | | |
| 4. Big data analytics | I4.0B-4 | | |
| 5. Cloud computing | I4.0B-5 | | |
| 6. Cyber security | I4.0B-6 | | |
| 7. Additive manufacturing | I4.0B-7 | | |
| 8. Simulation | I4.0B-8 | | |
| 9. Horizontal and vertical integration | I4.0B-9 | | |
| 10. Other enabling technologies (e.g., Energy technology) | I4.0B-10 | | |
| Automation Performance | AP | Ritzman and Safizadeh, 1999 | Adapted from 5-point to 7-point Likert scale |
| 1. Tool change. | AP-1 | | |

| Item | Label | Source | Operationalisation |
|---|---|---|---|
| 2. Job set up. | AP-2 | | |
| 3. Job or product processing. | AP-3 | | |
| 4. Process monitoring | AP-4 | | |
| 5. Process inspection | AP-5 | | |
| 6. Material movement | AP-6 | | |
| Production Cost Performance | CP | Wong, Boon-itt and Wong, 2011 | Adapted from 5-point to 7-point Likert scale |
| 1. Produces products with low costs. | CP-1 | | |
| 2. Produces products with low inventory costs. | CP-2 | | |
| 3. Produces products with low overhead costs. | CP-3 | | |
| 4. Offers price as low as or lower than our competitors. | CP-4 | | |
| Environmental Performance | EP | Zhu and Sarkis, 2004 | Adapted from 5-point to 7-point Likert scale |
| 1. Reduction of air emissions. | EP-1 | | |
| 2. Reduction of wastewater. | EP-2 | | |
| 3. Reduction of solid waste. | EP-3 | | |
| 4. Decrease of consumption for hazardous/harmful/toxic materials. | EP-4 | | |
| 5. Decrease of frequency of environmental accidents. | EP-5 | | |
| 6. Improve the enterprise's environmental situation. | EP-6 | | |

| Item | Label | Source | Operationalisation |
|---|---|---|---|
| Schedule Attainment Performance | SP | Bozarth et al, 2009 | Adapted from 5-point to 7-point Likert scale |
| 1. We usually meet the production schedule each day | SP-1 | | |
| 2. Our daily schedule is completed on time. | SP-2 | | |
| 3. We cannot adhere to our schedule on a daily basis. | SP-3 | | |
| 4. It seems as if we are always behind schedule. | SP-4 | | |

### *Appendix I: Missing Value Analysis*

| Univariate Statistics | | | | | | | |
|---|---|---|---|---|---|---|---|
| | N | Mean | Std. Deviation | Missing | | No. of Extremes[a] | |
| | | | | Count | Percent | Low | High |
| I4.0Breadth_AMS | 320 | 1.51 | 0.686 | 0 | 0.0 | 0 | 0 |
| I4.0Breadth_AR | 320 | 1.26 | 0.553 | 0 | 0.0 | | |
| I4.0Breadth_IoT | 320 | 1.70 | 0.732 | 0 | 0.0 | 0 | 0 |
| I4.0Breadth_BDA | 320 | 1.81 | 0.780 | 0 | 0.0 | 0 | 0 |
| I4.0Breadth_CC | 320 | 1.91 | 0.684 | 0 | 0.0 | 0 | 0 |
| I4.0Breadth_CS | 320 | 2.10 | 0.625 | 0 | 0.0 | 0 | 0 |
| I4.0Breadth_AM | 320 | 1.61 | 0.780 | 0 | 0.0 | 0 | 0 |
| I4.0Breadth_S | 320 | 1.47 | 0.725 | 0 | 0.0 | 0 | 0 |
| I4.0Breadth_HandV | 320 | 1.50 | 0.743 | 0 | 0.0 | 0 | 0 |
| I4.0Breadth_energy | 320 | 1.60 | 0.761 | 0 | 0.0 | 0 | 0 |
| Design_Manufacturing_Integration_1 | 320 | 5.47 | 1.211 | 0 | 0.0 | 16 | 0 |
| Design_Manufacturing_Integration_2 | 320 | 5.21 | 1.242 | 0 | 0.0 | 29 | 0 |
| Design_Manufacturing_Integration_3 | 320 | 4.80 | 1.565 | 0 | 0.0 | 11 | 0 |
| Design_Manufacturing_Integration_4 | 320 | 5.78 | 1.262 | 0 | 0.0 | 8 | 0 |
| Design_Manufacturing_Integration_5 | 320 | 4.66 | 1.407 | 0 | 0.0 | 4 | 0 |
| Design_Manufacturing_Integration_6 | 320 | 3.53 | 1.797 | 0 | 0.0 | 0 | 0 |
| Manufacturing_Strategy_Integration_1 | 320 | 5.55 | 1.253 | 0 | 0.0 | 23 | 0 |
| Manufacturing_Strategy_Integration_2 | 320 | 5.44 | 1.159 | 0 | 0.0 | 21 | 0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Manufacturing_Strategy_Integration_3 | 320 | 5.36 | 1.247 | 0 | 0.0 | 31 | 0 |
| Manufacturing_Strategy_Integration_4 | 320 | 4.95 | 1.622 | 0 | 0.0 | 10 | 0 |
| Manufacturing_Strategy_Integration_5 | 320 | 5.23 | 1.275 | 0 | 0.0 | 33 | 0 |
| Manufacturing_Strategy_Integration_6 | 320 | 5.24 | 1.271 | 0 | 0.0 | 28 | 0 |
| Systems_Integration_1 | 320 | 4.98 | 1.492 | 0 | 0.0 | 10 | 0 |
| Systems_Integration_2 | 320 | 4.65 | 1.517 | 0 | 0.0 | 10 | 0 |
| Systems_Integration_3 | 320 | 4.72 | 1.608 | 0 | 0.0 | 17 | 0 |
| Systems_Integration_4 | 320 | 4.98 | 1.619 | 0 | 0.0 | 17 | 0 |
| Systems_Integration_5 | 320 | 4.78 | 1.574 | 0 | 0.0 | 13 | 0 |
| Automation_1 | 320 | 3.04 | 1.609 | 0 | 0.0 | 0 | 0 |
| Automation_2 | 320 | 3.21 | 1.618 | 0 | 0.0 | 0 | 5 |
| Automation_3 | 320 | 3.91 | 1.591 | 0 | 0.0 | 0 | 0 |
| Automation_4 | 320 | 4.00 | 1.716 | 0 | 0.0 | 0 | 0 |
| Automation_5 | 320 | 3.35 | 1.744 | 0 | 0.0 | 0 | 0 |
| Automation_6 | 320 | 3.59 | 1.767 | 0 | 0.0 | 0 | 0 |
| Schedule_Attainment_1 | 320 | 5.43 | 1.479 | 0 | 0.0 | 41 | 0 |
| Schedule_Attainment_2 | 320 | 5.35 | 1.422 | 0 | 0.0 | 40 | 0 |
| Schedule_Attainment_3 | 320 | 4.67 | 1.815 | 0 | 0.0 | 0 | 0 |
| Schedule_Attainment_4 | 320 | 4.80 | 1.850 | 0 | 0.0 | 0 | 0 |
| Environmental_Sustainability_1 | 320 | 4.61 | 1.586 | 0 | 0.0 | 16 | 0 |
| Environmental_Sustainability_2 | 320 | 4.78 | 1.679 | 0 | 0.0 | 18 | 0 |
| Environmental_Sustainability_3 | 320 | 4.84 | 1.685 | 0 | 0.0 | 18 | 0 |
| Environmental_Sustainability_4 | 320 | 5.03 | 1.647 | 0 | 0.0 | 14 | 0 |
| Environmental_Sustainability_5 | 320 | 5.35 | 1.457 | 0 | 0.0 | 26 | 0 |
| Environmental_Sustainability_6 | 320 | 5.16 | 1.472 | 0 | 0.0 | 10 | 0 |
| Cost_1 | 320 | 4.55 | 1.647 | 0 | 0.0 | 0 | 0 |
| Cost_2 | 320 | 4.50 | 1.623 | 0 | 0.0 | 0 | 0 |
| Cost_3 | 320 | 4.60 | 1.591 | 0 | 0.0 | 0 | 0 |
| Cost_4 | 320 | 4.31 | 1.598 | 0 | 0.0 | 0 | 0 |
| Factory Size | 320 | | | 0 | 0.0 | | |
| **Production Strategy** | 320 | | | 0 | 0.0 | | |

**a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).**

## *Appendix J: Mahalanobis Distance and Outlier test*

| Observation number | Mahalanobis Distance ($D^2$) | p1 | p2 |
|---|---|---|---|
| **68** | 108.669 | .000 | .000 |
| **128** | 106.142 | .000 | .000 |
| **160** | 105.506 | .000 | .000 |
| **129** | 100.156 | .000 | .000 |
| **154** | 89.906 | .000 | .000 |
| **122** | 88.172 | .000 | .000 |
| **127** | 86.568 | .000 | .000 |

| | | | |
|---|---|---|---|
| **79** | 84.573 | .000 | .000 |
| **146** | 83.354 | .000 | .000 |
| **5** | 83.174 | .000 | .000 |
| **72** | 82.583 | .000 | .000 |
| **31** | 80.271 | .000 | .000 |
| **178** | 77.741 | .000 | .000 |
| **218** | 77.638 | .000 | .000 |
| **207** | 76.756 | .000 | .000 |
| **81** | 72.503 | .001 | .000 |
| **245** | 72.222 | .001 | .000 |
| **173** | 71.843 | .001 | .000 |
| **90** | 69.537 | .003 | .000 |
| **71** | 68.609 | .003 | .000 |
| **66** | 67.493 | .004 | .000 |
| **83** | 67.335 | .004 | .000 |
| **33** | 67.237 | .004 | .000 |
| **186** | 64.773 | .008 | .000 |
| **107** | 63.852 | .010 | .000 |
| **272** | 63.261 | .011 | .000 |
| **84** | 63.190 | .011 | .000 |
| **100** | 62.865 | .012 | .000 |
| **2** | 62.714 | .012 | .000 |
| **222** | 62.541 | .013 | .000 |
| **133** | 62.099 | .014 | .000 |
| **151** | 61.668 | .015 | .000 |
| **51** | 60.588 | .019 | .000 |
| **87** | 59.877 | .022 | .000 |
| **279** | 59.599 | .024 | .000 |
| **58** | 58.642 | .029 | .000 |
| **13** | 58.122 | .032 | .000 |
| **61** | 58.107 | .032 | .000 |
| **48** | 57.834 | .034 | .000 |
| **241** | 57.698 | .035 | .000 |
| **120** | 57.552 | .036 | .000 |
| **34** | 56.621 | .043 | .000 |
| **130** | 56.512 | .043 | .000 |
| **115** | 56.188 | .046 | .000 |
| **86** | 56.036 | .047 | .000 |
| **290** | 56.033 | .048 | .000 |
| **167** | 55.583 | .052 | .000 |
| **4** | 55.205 | .055 | .000 |
| **150** | 55.170 | .056 | .000 |
| **277** | 54.884 | .059 | .000 |
| **118** | 54.120 | .067 | .000 |
| **53** | 53.913 | .070 | .000 |
| **196** | 53.865 | .070 | .000 |
| **188** | 53.786 | .071 | .000 |

| | | | |
|---|---|---|---|
| **238** | 53.692 | .073 | .000 |
| **98** | 53.635 | .073 | .000 |
| **38** | 53.296 | .078 | .000 |
| **292** | 52.750 | .085 | .000 |
| **253** | 52.682 | .086 | .000 |
| **318** | 52.348 | .091 | .000 |
| **140** | 52.167 | .094 | .000 |
| **88** | 52.153 | .094 | .000 |
| **29** | 52.003 | .097 | .000 |
| **187** | 51.436 | .106 | .000 |
| **78** | 51.365 | .107 | .000 |
| **91** | 51.091 | .112 | .000 |
| **280** | 51.039 | .113 | .000 |
| **16** | 50.976 | .114 | .000 |
| **64** | 50.944 | .115 | .000 |
| **114** | 50.940 | .115 | .000 |
| **204** | 50.902 | .116 | .000 |
| **281** | 50.891 | .116 | .000 |
| **124** | 50.656 | .120 | .000 |
| **69** | 50.502 | .123 | .000 |
| **210** | 50.344 | .127 | .000 |
| **60** | 50.134 | .131 | .000 |
| **169** | 49.855 | .137 | .000 |
| **191** | 49.347 | .148 | .000 |
| **36** | 49.216 | .151 | .000 |
| **97** | 49.172 | .152 | .000 |
| **95** | 48.667 | .164 | .000 |
| **63** | 48.514 | .167 | .000 |
| **12** | 48.240 | .174 | .000 |
| **282** | 48.200 | .175 | .000 |
| **255** | 48.161 | .176 | .000 |
| **1** | 48.131 | .177 | .000 |
| **283** | 48.098 | .178 | .000 |
| **49** | 47.941 | .182 | .000 |
| **216** | 47.934 | .182 | .000 |
| **104** | 47.915 | .182 | .000 |
| **152** | 47.548 | .192 | .000 |
| **89** | 47.436 | .195 | .000 |
| **289** | 47.372 | .197 | .000 |
| **303** | 47.359 | .197 | .000 |
| **123** | 47.113 | .204 | .000 |
| **194** | 47.050 | .206 | .000 |
| **185** | 46.869 | .211 | .000 |
| **147** | 46.490 | .223 | .000 |
| **85** | 46.365 | .226 | .000 |
| **21** | 46.026 | .237 | .001 |

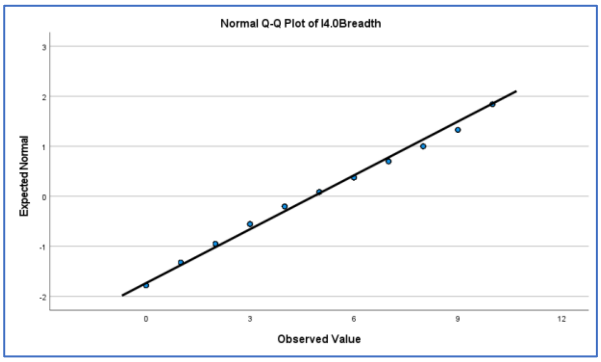
= Cases also experiencing z-scores > 3.29

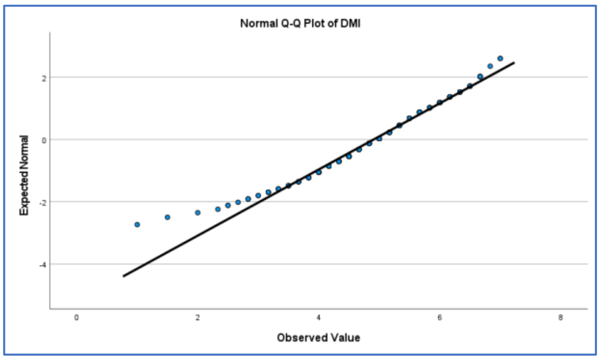
## *Appendix K: Assessment of Normality*

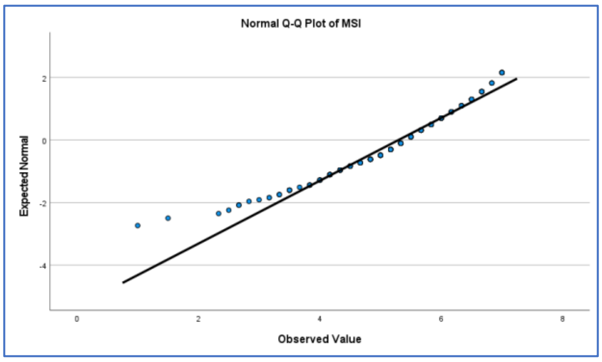
| Variable | min | max | skew | c.r. | kurtosis | c.r. |
|---|---|---|---|---|---|---|
| I4.0Breadth_energy | 1.000 | 3.000 | .804 | 5.875 | -.825 | -3.011 |
| I4.0Breadth_HandV | 1.000 | 3.000 | 1.093 | 7.979 | -.332 | -1.214 |
| I4.0Breadth_S | 1.000 | 3.000 | 1.208 | 8.822 | -.051 | -.185 |
| I4.0Breadth_AM | 1.000 | 3.000 | .804 | 5.872 | -.897 | -3.274 |
| I4.0Breadth_CS | 1.000 | 3.000 | -.074 | -.540 | -.477 | -1.743 |
| I4.0Breadth_CC | 1.000 | 3.000 | .120 | .876 | -.862 | -3.148 |
| I4.0Breadth_BDA | 1.000 | 3.000 | .351 | 2.567 | -1.274 | -4.651 |
| I4.0Breadth_IoT | 1.000 | 3.000 | .525 | 3.833 | -.982 | -3.586 |
| I4.0Breadth_AR | 1.000 | 3.000 | 2.037 | 14.875 | 3.080 | 11.248 |
| I4.0Breadth_AMS | 1.000 | 3.000 | .978 | 7.141 | -.298 | -1.089 |
| Systems_Integration_5 | 1.000 | 7.000 | -.742 | -5.416 | -.199 | -.728 |
| Systems_Integration_1 | 1.000 | 7.000 | -.904 | -6.604 | .247 | .900 |
| Systems_Integration_2 | 1.000 | 7.000 | -.587 | -4.288 | -.435 | -1.590 |
| Systems_Integration_3 | 1.000 | 7.000 | -.724 | -5.290 | -.244 | -.891 |
| Systems_Integration_4 | 1.000 | 7.000 | -.946 | -6.906 | .137 | .502 |
| Schedule_Attainment_4 | 1.000 | 7.000 | -.579 | -4.226 | -.869 | -3.173 |
| Schedule_Attainment_3 | 1.000 | 7.000 | -.492 | -3.590 | -1.022 | -3.733 |
| Schedule_Attainment_2 | 1.000 | 7.000 | -1.163 | -8.495 | .993 | 3.626 |
| Schedule_Attainment_1 | 1.000 | 7.000 | -1.197 | -8.744 | 1.002 | 3.657 |
| Automation_6 | 1.000 | 7.000 | .069 | .501 | -1.072 | -3.915 |
| Automation_5 | 1.000 | 7.000 | .163 | 1.191 | -1.029 | -3.758 |
| Automation_4 | 1.000 | 7.000 | -.133 | -.973 | -.905 | -3.305 |
| Automation_3 | 1.000 | 7.000 | -.142 | -1.035 | -.620 | -2.266 |
| Automation_2 | 1.000 | 7.000 | .165 | 1.202 | -.925 | -3.379 |
| Automation_1 | 1.000 | 7.000 | .278 | 2.033 | -.810 | -2.959 |
| Environmental_Sustainability_6 | 1.000 | 7.000 | -.885 | -6.465 | .493 | 1.801 |
| Environmental_Sustainability_5 | 1.000 | 7.000 | -1.152 | -8.417 | 1.218 | 4.448 |
| Environmental_Sustainability_4 | 1.000 | 7.000 | -.832 | -6.076 | -.102 | -.372 |
| Environmental_Sustainability_3 | 1.000 | 7.000 | -.724 | -5.289 | -.315 | -1.149 |
| Environmental_Sustainability_2 | 1.000 | 7.000 | -.673 | -4.913 | -.371 | -1.354 |
| Environmental_Sustainability_1 | 1.000 | 7.000 | -.563 | -4.114 | -.345 | -1.260 |
| Cost_4 | 1.000 | 7.000 | -.306 | -2.233 | -.687 | -2.508 |
| Cost_3 | 1.000 | 7.000 | -.400 | -2.918 | -.886 | -3.236 |
| Cost_2 | 1.000 | 7.000 | -.428 | -3.123 | -.834 | -3.045 |
| Cost_1 | 1.000 | 7.000 | -.481 | -3.516 | -.799 | -2.917 |
| Manufacturing_Strategy_Integration_1 | 1.000 | 7.000 | -1.132 | -8.269 | 1.568 | 5.724 |
| Manufacturing_Strategy_Integration_2 | 1.000 | 7.000 | -1.111 | -8.116 | 1.768 | 6.456 |
| Manufacturing_Strategy_Integration_3 | 1.000 | 7.000 | -.889 | -6.490 | .579 | 2.113 |

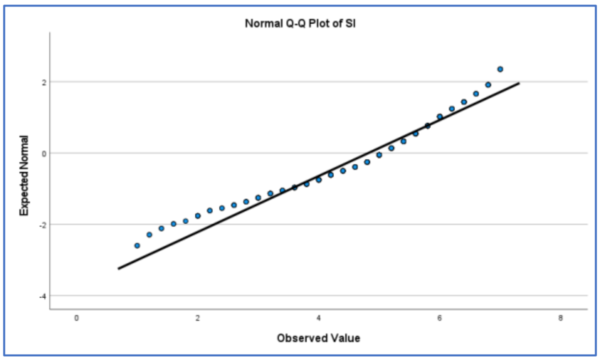
| | | | | | | |
|---|---|---|---|---|---|---|
| Manufacturing_Strategy_Integration_4 | 1.000 | 7.000 | -.754 | -5.503 | -.302 | -1.101 |
| Manufacturing_Strategy_Integration_5 | 1.000 | 7.000 | -.820 | -5.990 | .544 | 1.986 |
| Manufacturing_Strategy_Integration_6 | 1.000 | 7.000 | -.740 | -5.402 | .509 | 1.860 |
| Design_Manufacturing_Integration_1 | 1.000 | 7.000 | -.974 | -7.113 | 1.443 | 5.270 |
| Design_Manufacturing_Integration_2 | 1.000 | 7.000 | -.778 | -5.685 | .601 | 2.193 |
| Design_Manufacturing_Integration_3 | 1.000 | 7.000 | -.566 | -4.133 | -.386 | -1.409 |
| Design_Manufacturing_Integration_4 | 1.000 | 7.000 | -1.222 | -8.923 | 1.380 | 5.039 |
| Design_Manufacturing_Integration_5 | 1.000 | 7.000 | -.253 | -1.846 | -.457 | -1.669 |
| Design_Manufacturing_Integration_6 | 1.000 | 7.000 | .261 | 1.904 | -1.097 | -4.004 |
| Multivariate | | | | | 254.132 | 33.492 |

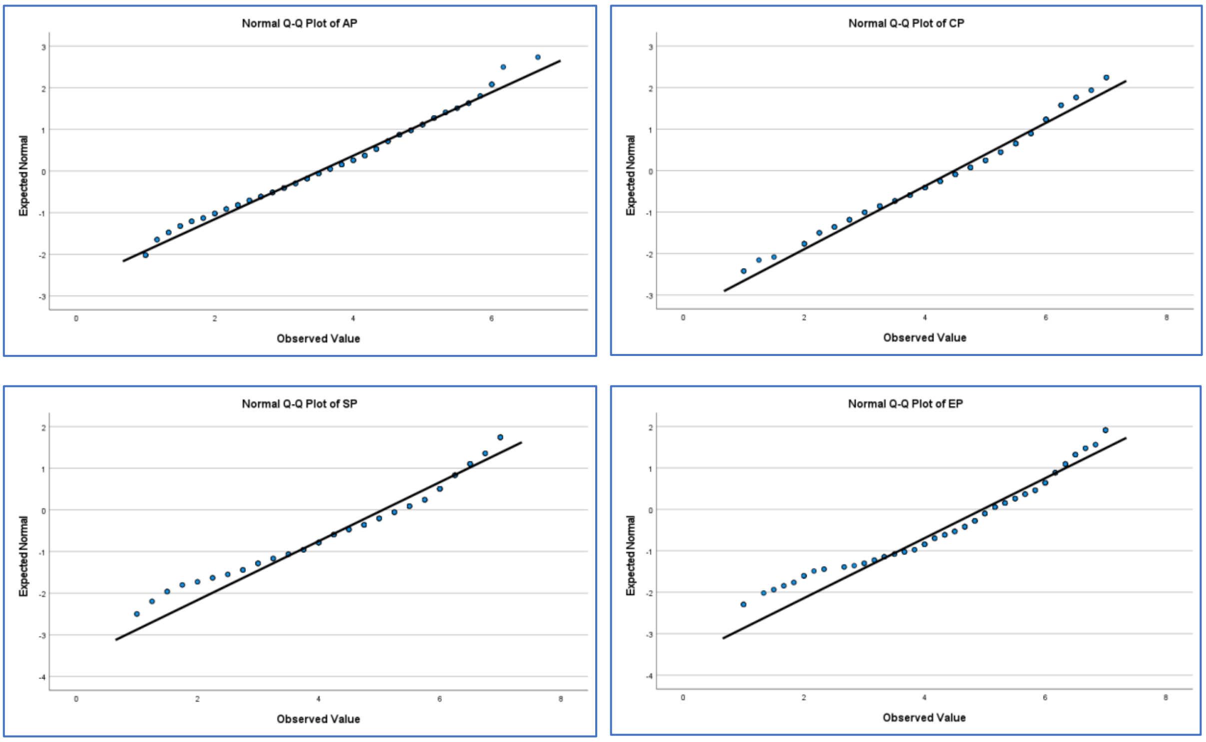
## *Appendix L: Multivariate normality test (Q-Q plots)*



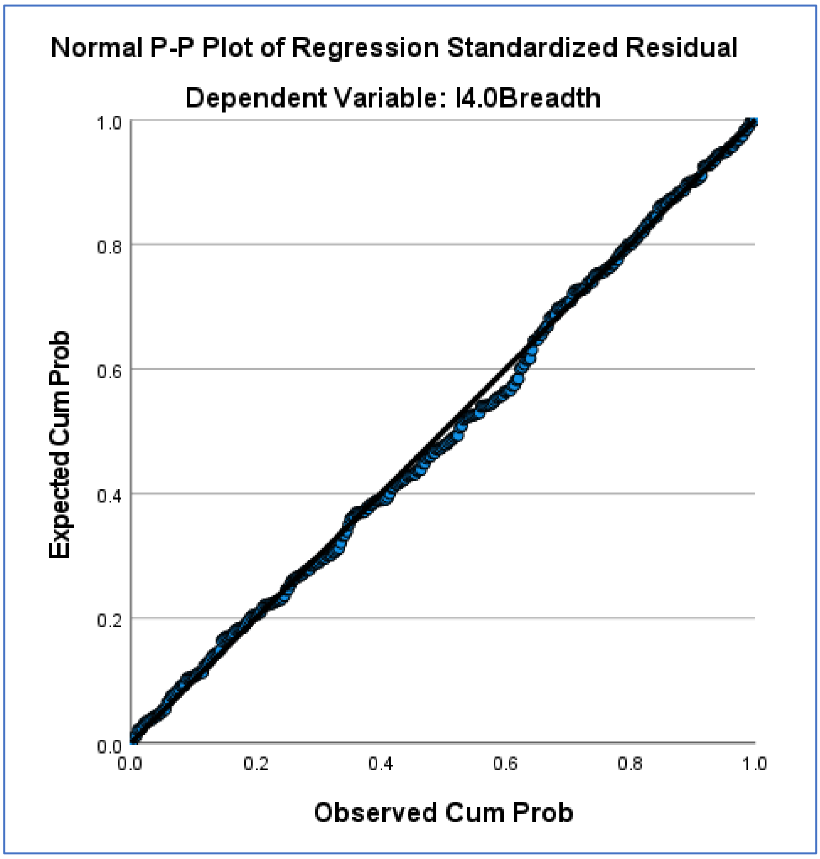



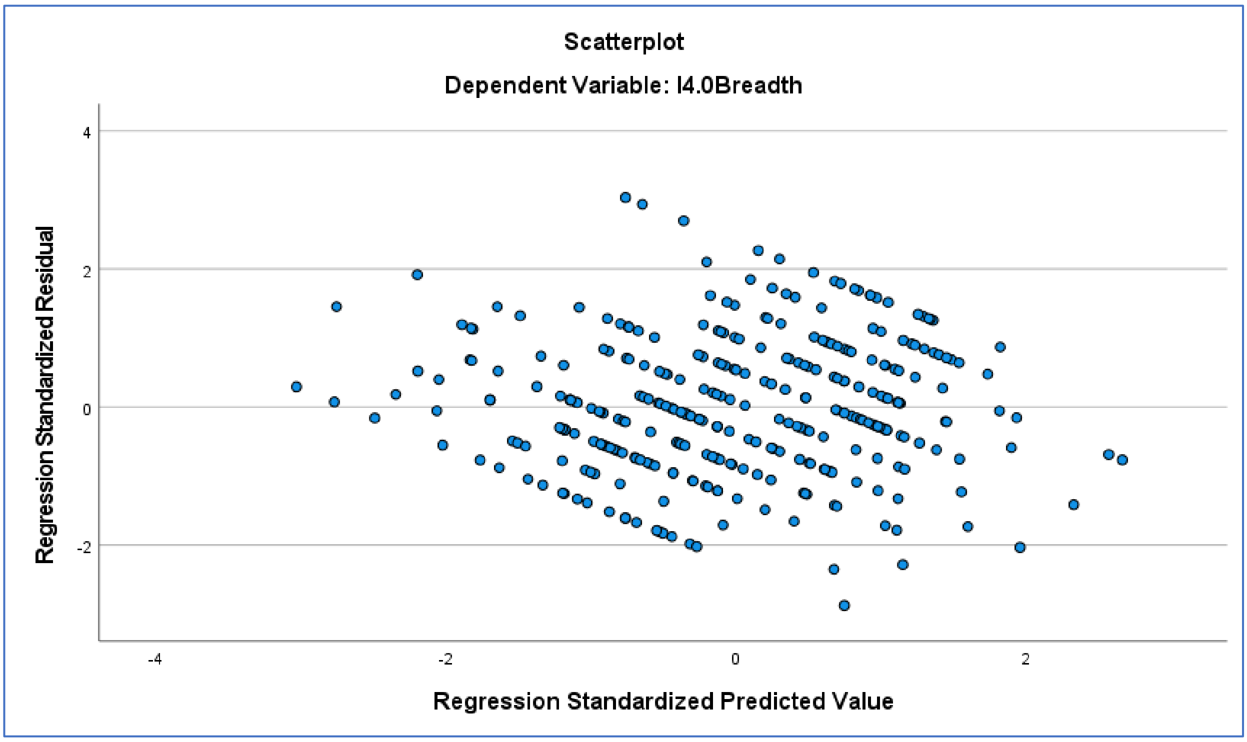






*Appendix M: Linearity test (P-P plots)*




Scatterplot
Dependent Variable: I4.0Breadth
Regression Standardized Residual
Regression Standardized Predicted Value
4
2
0
-2
-4
-2
0
2