Lean Manufacturing principles as a Driver for Digital Transformation: Adoption Insights and Performance Outcomes in Turkish SMEs

A Thesis Submitted for the Degree of Doctor of Philosophy

By

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2025

Abstract

Manufacturing companies have started to embrace Digital Transformation (DT) technologies to stay competitive and enhance their operational performance. However, the real industry implementation of DT technologies has proven challenging, particularly for small and medium-sized enterprises (SMEs) that face unique obstacles, especially within developing countries like Turkey. To improve the success rate, recent studies have been investigating the role of Lean Manufacturing (LM) principles to aid the adoption of DT technologies. Despite this interest, research on how LM principles can support DT adoption remains limited, particularly for SMEs. While larger corporations with greater resources are more frequently studied, SMEs often fall behind in DT adoption. Addressing this gap, this study examines how LM principles can aid Turkish manufacturing SMEs in adopting DT technologies, with the goal of improving their operational performance.

The theoretical lens of this research is institutional theory supported with contingency theory, to provide a more comprehensive understanding of DT technology adoption within SMEs in a developing country. While institutional theory offers valuable insights as one of the primary theoretical lenses of DT, existing research indicates that it often overlooks the specific challenges SMEs encounter in dynamic and diverse environments like manufacturing. To address this limitation, contingency theory is incorporated into the framework. As a result, the theoretical model is based on institutional theory, reinforced by contingency theory, to examine the impact of LM principles on the adoption of DT technologies in Turkish SMEs, with the goal of enhancing operational performance. Developing and validating this theoretical framework not only deepens the understanding of DT adoption in SMEs but also expands the institutional theory by establishing a robust model tailored to a more complex environment with specific needs and challenges of SMEs in developing countries.

To accomplish the research objectives, this study adopted a quantitative research approach. A questionnaire survey was administered, with responses collected from 208 participants representing Turkish SMEs. Following data collection, quantitative analysis was conducted using Structural Equation Modelling (SEM) with IBM SPSS and AMOS software. The SEM analysis results indicate that LM principles positively influence the adoption of DT technologies within Turkish SMEs, providing insights

into the specific LM principles that drive this impact. Additionally, the analysis revealed that institutional pressures, specifically mimetic, coercive, and normative pressures arising from competitors, government regulations, and industry further supported DT adoption in Turkey. The findings also provide evidence that DT technologies contribute to improved operational performance within Turkish SMEs.

This research offers empirical evidence that LM principles support DT technology adoption in Turkish SMEs, providing valuable insights into how LM principles can contribute to DT adoption processes. From a theoretical perspective, the study extends the institutional theory framework by adapting it to more complex environments through the integration of contingency theory. Additionally, the findings provide practical guidance for managers on aligning their strategies to facilitate DT adoption and inform policymakers on the effects of creating supportive policies that enhance DT adoption among SMEs.

Declaration

I hereby declare that this thesis is based on my original work, except where quotations and citations are duly acknowledged. Also, to the best of my knowledge and belief, no part of the work referred to in this thesis has been submitted in support of an application for any other degree or qualification at Brunel University or any other university or institution of learning.

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List of Abbreviations

AI	Artificial Intelligence
ASV	Average Shared Variance
AVE	Average Variance Extracted
CAD	Computer Aided Design
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
DT	Digital Transformation
EFA	Explanatory Factor Analysis
GDP	Gross Domestic Product
GOF	Goodness of Fit Index
IoT	Internet of Things
JIT	Just-in-Time
KOSGEB	Küçük ve Orta Ölçekli İşletmeleri Geliştirme ve Destekleme İdaresi Başkanlığı (Small and Medium Enterprises Development Organization of Türkiye)
LM	LM Lean Manufacturing
MSV	Maximum Shared Variance
OB	Organisational Behaviour
SEM	Structural Equation Modelling
SLR	Systematic Literature Review
SMEs	Small and Medium-sized Enterprises
TPS	Toyota Production System
TÜBİSAD	Türkiye Bilişim Sanayicileri Derneği (Turkish Informatics Industry Association)
VSM	Value Stream Mapping

Chapter 1: Introduction

1.1. Research Background

The increasing adoption of digital technologies has brought transformative advantages across the manufacturing sector enhancing value creation, productivity to significant cost reductions (Matt, Hess and Benlian, 2015). The integration of digital technologies, also known as Digital Transformation (DT) provide significant benefits to manufacturing companies (Fitzgerald *et al.*, 2013), with operational benefits such as lower inventory levels, reduced lead times, improved quality, and heightened productivity (Tortorella, Giglio and van Dun, 2019; Calabrese *et al.*, 2020). A recent study revealed that small and medium-sized enterprises (SMEs) benefit from DT technologies on 14 different dimensions ranging from increased customer satisfaction to cost reduction (Pfister and Lehmann, 2023). With the significant benefits and opportunities that DT technologies present, it is also becoming critical to survival for manufacturing (Govindarajan and Immelt, 2019). Studies have shown that companies consider DT crucial for the future of their organization, with research revealing that 78% of respondents believe it is essential for their survival (Fitzgerald *et al.*, 2013; Mazzone, 2014; Siebel and Rice, 2019). Consequently, it is imperative for manufacturing companies to embrace DT technologies not only to leverage these benefits but also to ensure their survival in the increasingly competitive manufacturing environment.

While the benefits look promising, the adoption of DT technologies has proven challenging, with a relatively low success rate (Yilmaz *et al.*, 2022; Sony *et al.*, 2024). The studies focusing on DT show that around 70-90% of the DT initiatives were unsuccessful and fail to meet their intended objectives (Bucy, 2016; Ramesh and Delen, 2021). While DT technologies are difficult to implement even for large corporations, the challenge is even greater for SMEs due to their limited resources, risk-averse nature, and generally lower expertise levels (Ghobakhloo and Fathi, 2020; Telukdarie *et al.*, 2022). Implementing DT technologies in SMEs is crucial for fully harnessing the benefits of DT across the broader manufacturing landscape, as SMEs serve as the backbone of many countries, making up 99% of businesses in Europe and accounting for 70% of the global workforce. (WEF, 2022; Eurostat, 2023). Analysing the failure rates for DT initiatives, studies have shown that SMEs face different challenges and obstacles compared to large enterprises when adopting DT technologies (Ericson *et al.*, 2020; Masood and Sonntag, 2020). Due to these specific challenges, they require a tailored approach that incorporates their unique characteristics and resource constraints (Battistoni *et al.*, 2023). Hence, while SME adoption of DT is vital for broader economic benefits, their high failure rate highlights the need for a tailored approach to boost adoption.

The adoption of DT technologies in SMEs in developing countries is particularly complex (Matt, Modrák and Zsifkovits, 2020; Elhusseiny and Crispim, 2021). Companies in these countries face different pressures that shape their manufacturing landscape, such as resource constraints, regulatory demands, and competition, typically resulting in lower levels of technology adoption and employee skills compared to developed countries (Sukrat and Leeraphong, 2024). As a developing country, Turkey's manufacturing companies encounter external pressures such as limited financial resources, compliance with varying regulations, and increased market competition, complicating the adoption of DT technologies in contrast to their counterparts in developed nations manufacturing sector accounting for 22% of the GDP in 2022 (The World Bank, 2024). Although the process is more challenging, the potential benefit is higher, as DT technologies can stimulate export-driven growth and significantly enhance the economies of developing countries (Ndulu *et al.*, 2023). With SMEs contributing 70% of GDP in developing countries, DT adoption offers essential benefits to the broader manufacturing landscape (WEF, 2022). This is further supported by the study by Bogoviz *et al.*, (2019), which highlighted the benefits of DT technologies and emphasized the need for a different approach to address the challenges faced by developing countries. However, the research mostly focuses on developed nations, leaving a gap in understanding DT adoption challenges for SMEs in developing countries (Raj *et al.*, 2020; Telukdarie *et al.*, 2022). Given the critical role of SMEs in developing countries like Turkey, a tailored solution is needed to address their challenges and improve the high failure rate associated with DT technology adoption (Das, Kundu and Bhattacharya, 2020; Raj *et al.*, 2020; WEF, 2022). Tailored solutions also need to consider the specific context of each country, as the wide diversity among developing nations means that findings highlight a need for a country-specific approach and an analysis of external pressures (Karakaya, Alataş and Yılmaz, 2020).

Over the last years, Lean Manufacturing (LM) principles have emerged as possible solution to help the adoption of DT technologies and improve the success rate (Dombrowski, Richter and Krenkel, 2017; Bittencourt, Alves and Leão, 2020). The foundation of LM is based by Tachi Ohno, as a method to increase customer value through higher quality, reduced cost, and less delivery time (Ohno, 1988). LM and DT share the same goal of increased value delivered to the customer (Prinz, Kreggenfeld and Kuhlenkötter, 2018). Although LM principles are a contender to support the adoption of DT technologies, gaps remain in the literature regarding this context, as the relationship between LM principles and DT technologies is yet to be clearly defined, and research in this area is ongoing (Moraes, Carvalho and Sampaio, 2023; Frank *et al.*, 2024). Overall, studies showed that there is a synergetic relationship between LM and DT (Mrugalska *et al.*, 2017; Lorenz *et al.*, 2018; Mayr *et al.*, 2018; Powell, Morgan and Howe, 2021) and highlighted positive impact of LM principles on adoption of DT technologies (Mofolasayo *et al.*, 2022). However, these studies had limitations constrained their ability to fully uncover the extent to which LM principles influence the adoption of DT technologies and its effect on operational performance (Bittencourt, Alves and Leão, 2020; Narula *et al.*, 2023). Addressing these literature gaps is essential for comprehending how LM principles can help the adoption of DT technologies in the manufacturing landscape and for realizing their full potential while reducing the failure rate (Rossini *et al.*, 2021).

One of the primary gaps identified in LM principles helping DT adoption is the absence of a comprehensive conceptual framework demonstrating the impact of LM principles on DT technologies (Kolberg *et al.*, 2017; Bittencourt, Alves and Leão, 2020). To examine the impact of LM principles on the adoption of DT technologies, it is first necessary to conceptualize their relationship (Rossini *et al.*, 2019). Although some frameworks exist, they are not comprehensive, encompassing only a limited range of LM principles or DT technologies and lacking the statistical validation required for a thorough understanding (Ciano *et al.*, 2021). Given the principles of LM and the various technologies in DT, it is important to examine their integration to understand potential interactions and support mechanisms (Dixit, Jakhar and Kumar, 2022). Thus, to address this research gap identified by research (Kolberg *et al.*, 2017; Rossini *et al.*, 2019; Bittencourt, Alves and Leão, 2020; Ciano *et al.*, 2021), firstly a framework is needed to be proposed. in this study, through an extensive literature review that includes a systematic literature review, a conceptual framework will be constructed.

Another gap in literature is that the available studies that focus on LM principles impact on DT technologies use need further empirical validation as they use small samples sizes (Pagliosa, Tortorella and Ferreira, 2019; Rossini *et al.*, 2019). A study by Rossini *et al.* (2021), which included 19 case studies, found that LM principles drive adoption of DT technologies in manufacturing companies. However, the small sample size in this study was identified as a limitation, preventing a more robust substantiation of the positive impact of LM principles on DT adoption. Similarly, the study by Ciano *et al.* (2021) focused on proposed a framework for LM principles impact on DT technologies and highlighted the need of research validating the impact explore the interrelationships between LM principles and DT technologies. This is further supported by bibliometric analysis done by Alsadi *et al.* (2023) which showed that studies on LM principles and DT technologies significantly lacked empirical validation. Overall, to address this research gap regarding lack of empirical results, the impact of LM principles on DT technologies and its subsequent effect to operational performance needs to be empirically validated through large sample studies, as highlighted by literature (Ciano *et al.*, 2021; Rossini *et al.*, 2021; Alsadi *et al.*, 2023). To address this gap, this study aims to empirically validate the proposed conceptual model by gathering data via an online questionnaire and utilizing Structural Equation Modeling (SEM) to explore the relationships between LM principles and DT technologies.

Recent studies have highlighted a significant research gap regarding the lack of an empirically established link between DT technologies and operational performance, especially in SMEs within developing countries (Dalenogare *et al.*, 2018; Raj *et al.*, 2020; Atieh, Cooke and Osiyevskyy, 2023). Furthermore, SMEs in developing countries face unique challenges in adopting DT compared to their counterparts in developed nations requiring a deeper and more contextual understanding of the operational impacts (Raj *et al.*, 2020). The differences in operational benefits between developed and developing countries have been analysed by Dalenogare *et al.* (2018) highlighting the need for broader examination in the context of developing countries. While some studies have concentrated on the advantages of DT technologies for SMEs in developing countries (Onu and Mbohwa, 2021; Ndulu *et al.*, 2023), a significant gap in empirical evidence remains due to limitations like small sample sizes and narrow research scopes (Shqair and Altarazi, 2022; Atieh, Cooke and Osiyevskyy, 2023). Understanding the benefits of DT technologies in SMEs within developing countries and their implications for the broader manufacturing sector is essential, and this study specifically focuses on Turkey to fill this identified research gap. Turkey have been chosen as focus of this study firstly because it is a typical developing country example in terms of GDP, income disparity, level of industrialisation and human aspects such as health and education has been often used as an example for developing country (Gergin *et al.*, 2019; Karakaya, Alataş and Yılmaz, 2020; Yüksel, 2020; United Nations, 2021; Hale, 2023). While developing countries have some common characteristics, it is crucial to consider the unique circumstances and external pressures specific to each country (Karakaya, Alataş and Yılmaz, 2020). Therefore, this study aims to propose and empirically test a conceptual framework within Turkish SMEs to address the gap regarding the impact of DT technologies in a developing country context and identify its unique country-specific external pressures.

Theoretically, the research focusing on LM and DT have primarily adopted institutional theory as the theoretical lens of their research (Punnakitikashem *et al.*, 2009; Sony and Aithal, 2020; Fogaça, Grijalvo and Neto, 2022). Institutional theory highlights that companies that are subjected to similar external pressures become similar and act in a similar way (Kauppi, 2022). However, over the years institutional theory alone has proven to have limitations to address the complexities of organizations, particularly in contexts requiring insights into diversity, strategic decision-making, and intricate environmental dynamics (Gupta *et al.*, 2020; Kelling *et al.*, 2021). In developing countries context, the limitations of institutional theory are often attributed to failing to clearly define boundaries or specify conditions, which results in generalizations that overlook specific contextual factors (Basu *et al.*, 2020). To address these shortcomings, integrating institutional theory with other frameworks, such as contingency theory, has proven effective, particularly in the context of DT (Aksom and Tymchenko, 2020; Aripin *et al.*, 2023). In this research, institutional theory is combined with contingency theory to further develop the theoretical framework. More specifically, institutional theory serves as the primary theoretical foundation, complemented by contingency theory, to illustrate the external pressures influencing the adoption of DT technologies through LM principles, ultimately aiming to improve operational performance in the Turkish SME environment.

Overall, DT technologies have a big potential to improve operational performance and help companies stay competitive in the manufacturing (Tortorella, Giglio and van Dun, 2019; Calabrese *et al.*, 2020). While SMEs represent a substantial portion of companies in manufacturing environment, they have fallen behind in the adoption of DT technologies and their associated advantages, especially in developing countries where these benefits are particularly important (Ghobakhloo and Iranmanesh, 2021; Ndulu *et al.*, 2023). To address this high failure rate, LM principles offer a potential solution (Bittencourt, Alves and Leão, 2020). However, there are gaps in the literature that prevent further exploration of this approach which is a lack of a comprehensive framework that integrates LM principles and DT technologies (Rossini *et al.*, 2019). Additionally, empirical validation of this model with a large sample is missing, which would allow for the exploration of the individual links between LM principles, DT technologies, and their subsequent impact on operational performance (Ciano *et al.*, 2021). Especially, the link between DT adoption and operational performance in SMEs in developing country context is missing (Dalenogare *et al.*, 2018). Theoretically, while the main theories that focus on DT and LM have been institutional and contingency theories (Punnakitikashem *et al.*, 2009), these need to be further developed to fully incorporate DT and LM principles more comprehensively.

1.2. Research Scope

This research focuses on SMEs within the Turkish manufacturing sector and narrowing its scope to internal manufacturing operations. LM originated in manufacturing sector, but its applications have expanded into various industries, including healthcare and food (Doğan and Unutulmaz, 2016; Gładysz, Buczacki and Haskins, 2020). Non-manufacturing SMEs are not included within the scope of this research to ensure the analysis remains directly aligned with the study's objectives and industrial context. Given the broad scope of LM and DT, it is essential to refine the research focus specifically on internal manufacturing operations, especially since both significantly impact areas beyond the traditional supply chain, supplier and customer relationships (Shah and Ward, 2003; Faruquee, Paulraj and Irawan, 2021). Hence, the scope of this research includes internal manufacturing operations and excludes other aspects of the supply chain and customer-related elements to provide a more concentrated approach. While elements such as logistics, supplier relationships, and customer interactions are integral to LM and are extensively discussed in SME-focused literature (Quiroz-Flores, Canales-Huaman and Gamio-Valdivia, 2022; Kosasih *et al.*, 2023; Dossou and Tchuenmegne, 2024), this study deliberately narrows its focus to internal manufacturing processes to provide a more focused and in-depth analysis.

Given the aim of increasing operational performance amongst manufacturing landscape, the focus on SMEs is pivotal. SMEs representing 99% of all businesses and accounting for approximately two-thirds of the manufacturing workforce in Europe (Eurostat, 2023). As a good representative, Turkey has high level of manufacturing activity where more than 90% of SMEs and shows signs of a typical that play a substantial role (TÜİK, 2023). Given these characteristics, Turkey's economic and industrial landscape offers a unique environment and opportunity for exploring the DT technology adoption (Yüksel, 2020). Furthermore, while classification of an SME can vary between countries, according to European Comission (2021), there are two criteria which are employee count and yearly turnover or balance sheet total. More specifically, to classify as an SME, a company needs to under the headcount of 250 and have either lower turnover of 50 M € or balance sheet of 43 M €. The scope of this research is limited to companies in manufacturing sector that abide with the European criteria. This research uses the EU Commission's definition to classify SMEs.

This research is country-specific, enabling a focused analysis of contextual factors that provide essential insights for creating tailored solutions to address the distinct challenges manufacturing companies face under various external pressures (Karakaya, Alataş and Yılmaz, 2020). Turkey, with its characteristics as a developing country and a robust manufacturing sector where awareness of digital technologies is particularly strong in the automotive, electrical, and machinery industries, has been selected as the focus for this research (Sarı, Güleş and Yiğitol, 2020). Turkish SMEs operate amid global economic challenges and geopolitical issues (Asgary, Ozdemir and Özyürek, 2020). Therefore, the research scope considers the economic, cultural, and social dynamics aligned with institutional theory, which influence business practices and shape the regulatory environment impacting technology adoption. The research further explores market characteristics and the specific challenges encountered by Turkish SMEs, enabling the framework to incorporate unique pressures and patterns within Turkey's DT adoption process

1.3. Research Aims and Objectives

The aim of the research is to investigate the impact of LM principles on adoption DT technologies Turkish manufacturing SMEs, where the study aims to show the role of LM principles in enhancing the adoption and implementation of DT technologies. LM is defined through a set of principles that removes waste and streamlines processes to add customer value (Rahardjo *et al.*, 2023). This streamlining creates a solid foundation for adopting DT technologies, which involve integrating digital tools and processes to improve operational performance measures such as turnaround time and quality (Fitzgerald *et al.*, 2013; Calabrese *et al.*, 2020). Hence, this research also seeks to analyse the impact of adopting DT technologies on operational performance. To fill the existing research gaps, the study will develop and empirically test a conceptual framework that shows how specific LM principles impact the adoption of DT technologies.

The aim can be broken down to the objectives below:

- To introduce and empirically verify a conceptual framework incorporating links between LM principles, DT technologies and operational performance,
- To empirically assess which LM principles has a positive impact on adoption of DT technologies in Turkish SMEs,
- To empirically assess and identify which DT technologies lead to operational performance improvement in Turkish SMEs,
- To identify the external pressures that affect the adoption of DT technologies in Turkish SMEs.

By achieving these aims, the research intends to provide insights that can help SMEs to improve the adoption rate of DT technologies thereby improving operational performance that will be also analysed in this study.

1.4. Research Questions

From the research aims and objectives, the following research questions were formulated:

RQ1. How do Lean Manufacturing principles affect the adoption digital transformation technologies within small and medium-sized manufacturing enterprises (SMEs) in Turkey?

RQ2. Which Lean Manufacturing principles positively the adoption of Digital Transformation technologies within Turkish manufacturing SMEs?

RQ3. How does adoption of Digital Transformation (DT) technologies affect operational performance outcomes in SMEs within the Turkish manufacturing landscape?

Through answering these questions this research aims to get insights to contribute to the understanding and enhancement of DT adoption in SMEs, particularly in the context of developing economies.

1.5. Intended Contribution

One of the primary contributions of this research is theoretical by expanding institutional theory with the integration of contingency theory, enabling it to better address the complexities faced by organizations in diverse environments. Institutional theory, often used to explain organizational behaviour, provides a framework for understanding how external pressures such as competition, norms, industry standards and policies affect organizations (Yin *et al.*, 2024). However, it has limitations in complex settings like manufacturing and DT, where rapidly changing technologies, standards, and policies add challenges, and assuming uniform responses from a wide range of companies often falls short of accurately capturing outcomes (Kelling *et al.*, 2021; Fogaça, Grijalvo and Neto, 2022; Gupta *et al.*, 2022). Despite experiencing similar institutional pressures, companies respond differently based on their size or sector (Bhatia and Kumar, 2022). This research seeks to contribute to theory by expanding the theory through challenging the notions of isomorphism and uniform responses among large groups. It emphasizes the role of contingency factors in understanding how organisations respond to these pressures in complex groups and fast-moving topics like DT.

This research intends to contribute to theory by proposing and validating an expanded theoretical framework for institutional theory through the integration of contingency theory. It aims to deepen the understanding of how organizations adopt DT technologies and their relationship with LM principles when facing similar external pressures, building on the theoretical foundation established in prior literature (Ketokivi and Schroeder, 2004; Bokrantz *et al.*, 2020; Vilkas *et al.*, 2022). By incorporating elements of contingency theory, the institutional framework is expanded to address its limitations (Fogaça, Grijalvo and Neto, 2022) and enhance its applicability across a broader range of contexts. This expanded framework enables future scholars to examine how various factors interact with institutional pressures to shape organizational behaviour, particularly in dynamic environments such as DT (Akenroye *et al.*, 2024).

This study aims to make several empirical contributions. First, it aims to contribute by proposing and validating a comprehensive conceptual framework that links DT technologies, LM principles, and operational performance. Through the collection of quantitative data and statistical analysis using SEM, this research seeks to provide empirical validation for a holistic framework, addressing a key gap identified in recent literature, particularly concerning the relationship between LM principles and DT technologies (Pagliosa, Tortorella and Ferreira, 2019; Rossini *et al.*, 2019). Second, it aims to empirically confirm the positive impact of LM principles on DT adoption in underexplored context of Turkish SMEs and validates the role of LM principles in facilitating DT adoption using a robust sample size. This aims to offer valuable insights and in-depth analysis into the role of LM principles in supporting the adoption of DT technologies. Third, the study aims to demonstrate how DT technology adoption impacts operational performance in Turkish SMEs, filling a notable research gap in developing countries where limited data is available (Raj *et al.*, 2020; Atieh, Cooke and Osiyevskyy, 2023). Finally, an important contribution of this research is its analysis of the effect of institutional pressures on DT adoption within Turkish SMEs, addressing the lack of consensus on how these pressures influence DT technology adoption, particularly those from policymakers and industry standards (Čater *et al.*, 2021; Kuo, Chen and Yang, 2022; Zhou and Zheng, 2023). Through this analysis, the study aims to contribute to the literature by providing insights into how current institutional pressures are shaping organizational behaviour and decision-making in companies

In addition to its theoretical and empirical contributions, this research offers valuable practical implications for managers and policymakers. For managers, it provides actionable insights for DT adoption strategies, supported by empirical evidence on the role of LM principles in supporting the adoption of DT technologies and addressing key challenges. From the insights of this research, managers can focus on LM principles that drive success, supported by practical examples and statistical analyses to aid evidence-based decision-making and secure management buy-in (Pfeffer and Sutton, 2006). Furthermore, it delivers tailored guidance to managers and policymakers in resource constrained environments, particularly for SMEs in developing countries like Turkey, where strategic resource allocation and risk management are critical (Ghobakhloo and Fathi, 2020). For policymakers, the study provides valuable insights into improving government support for SMEs, including initiatives like those implemented by KOSGEB in Turkey. Additionally, it aims insights to the Turkish government on policies to assess their effectiveness in facilitating DT adoption, ensuring they align with the specific needs and challenges of SMEs in the country.

1.6. Chapter Summary

While DT is highlighted with operational benefits and crucial for survival of manufacturing firms, its adoption has been challenging, especially for SMEs in developing countries (Onu and Mbohwa, 2021; Ndulu *et al.*, 2023). The previous literature identified LM principles positive influence on DT technologies adoption, where it can be a possible solution to this problem identified (Bittencourt, Alves and Leão, 2019). However, there are research gaps to explore this context further that are lack of a comprehensive framework, absence of empirical approval and a focused attention on SMEs in developing countries like Turkey (Raj *et al.*, 2020; Telukdarie *et al.*, 2022). This research aims to understand the impact of LM principles on adoption of DT technologies in SMEs in Turkey together in country specific context, to propose and empirically validate framework that cover LM principles, DT adoptions and operational performance. This study adopts institutional theory, complemented by contingency theory, as its theoretical framework, aiming to bridge a gap in the literature by extending the application of institutional theory to cover complex large groups such as Turkish manufacturing SMEs. This chapter provide the introductory foundation by outlining the background, objectives, scope and intended contributions of the study.

Chapter 2: Literature Review

2.1. Chapter Introduction

In this section, firstly Lean Manufacturing (LM) and Digital Transformation (DT) are explored in detail individually to provide a comprehensive understanding necessary for the context of this research. Firstly, LM is introduced with its framework, principles, and accompanying tools according to notable literature in the field (Liker, 2003; Shah and Ward, 2003; Hines, Holweg and Rich, 2004; Holweg, 2007; Åhlström *et al.*, 2021). Following the literature review on LM, DT is introduced, highlighting its associated technologies within manufacturing settings. The section focusing on DT technologies explains literature focusing on its benefits on operational performance and ends with exploring DT adoption in SMEs and Turkey. After introducing LM and DT individually, the literature concerning the integration of LM and DT are explained where the focus shifts to LM influence on adoption of DT technologies. This chapter will end with highlighting the gaps in literature and this research's contribution to existing literature.

2.2. Lean Manufacturing Principles

This section begins by introducing LM, starting from its historical context and a definition. As the widespread use and ongoing discussions on LM's definition is ongoing according to prominent researchers in the field it is crucial to thoroughly establish LM's context from a historical perspective for the purpose of this research (Cusumano *et al.*, 2021; Hopp and Spearman, 2021; Åhlström *et al.*, 2021). Following the definition, the section explains the LM framework, principles, and the specific tools associated with each principle, laying the groundwork for understanding LM's influence on DT technologies. When explaining principles, it provides a brief overview of how they are currently integrated with technology, highlighting the practical applications and connections between LM principles and technological advancements. Through this, this section provides the groundwork to understand the LM principles' impact on DT technologies.

2.2.1. Definition and Development

The origins of LM go back to Japanese automotive industry, more specifically Toyota Motor Corporation (Bicheno and Holweg, 2016). Taiichi Ohno, after joining Toyota Motor Corporation in 1943, faced problems such as large inventory, defects, and most importantly accompanying high cost. Mid-18th century included post-war, where resources were limited in Japan. To overcome these difficulties, Ohno developed set of principles and rules that formed the Toyota Production System (TPS) (Ohno, 1988; Holweg, 2007). To aid these principles, he developed tools such as Kanban to cut cost and tackled problems like the excess and unbalanced inventory (Sugimori *et al.*, 1977; Liker, 2020). TPS also included human-related principles where Ohno emphasised importance "respect for human" and put employees centre of the operations (Ohno, 1988). A comprehensive overview of TPS, its principles and the transition to Lean Manufacturing has been developed by the work of Liker (2003).

With the success of Toyota Motor Corporation, Western manufacturing world has started to notice the influence of TPS and started to analyse the tools and principles set out by Ohno (Bicheno and Holweg, 2016). Further, Krafcik (1988) described Western Mass Manufacturing as 'buffered production' where excess inventory was kept against various risks like quality issues. As a comparison, TPS was called 'lean' with bufferless minimum inventory levels that allowed detection of quality issues. The definition of Lean was further developed by Womack and Jones (2013) as "Lean is doing more with less. Use the least amount of effort, energy, equipment, time, facility space, materials, and capital – while giving customers exactly what they want".

The first time that "Lean Manufacturing" was coined was in the book "Machine that Changed the World" where Womack, Jones and Roos (1990) compared Western's Mass manufacturing with Japan's TPS. After recognition of LM, its expansion to supplier, customer and product management systems started to expand (Holweg, 2007). Shah and Ward (2007) divided the literature on LM into two segments, firstly as a philosophical approach that focuses on guiding principles and practical approach that focuses on application of tools. In 1990s, applications of LM mostly based in focused on application of tools rather than creating value and neglected human aspects that are critical to high performing companies (Hines, Holweg and Rich, 2004). A shift from this practical approach, Womack, Jones and Roos (1990) have developed a 'Lean Thinking' framework that moved the focus from operational performance improvements to a more comprehensive value focus (Hines, Holweg and Rich, 2004). In the book 'Lean Thinking' a general framework was introduced that can be applied to many settings (Womack and Jones, 2013).

Over the years, definition of Lean has become a very broad and discussed a throughout the academia. While its relation to other paradigms expands, the understanding becomes more diverse but also open to interpretation. In the late 1980s, Lean also became linked to the Shingo Excellence Model, created by Japanese industrial engineer Shigeo Shingo, which highlights the role of organisational culture in supporting the application of Lean principles, thus fostering transformation and continuous improvement to deliver the operational excellence. (Sá *et al.*, 2022). Further, combining Lean with Agility, the modern operational excellence is modern operational excellence is driven by a holistic combination of technology integration, data-driven decision-making, and cross-functional collaboration, enabling continuous improvement (Forbes, 2025). In today's business environment, agility integrates lean thinking with creativity and flexibility (Gartner, 2018), while resilience, combined with lean practices, supports swift adaptation to highly volatile and diverse markets, as illustrated by case studies (Habibi Rad, Mojtahedi and Ostwald, 2021). This evolution reflects an expansion of Lean's scope beyond its original manufacturing roots, incorporating complementary concepts such as agility and resilience in today's business environment.

Due to this expansion of scope, even after more than 30 years since the word "Lean" was coined, there are still active conversations on its definition going in reputable journals by prominent academics in the field (Cusumano *et al.*, 2021; Hopp and Spearman, 2021; Åhlström *et al.*, 2021). Due to this ongoing ambiguity, it is important to clearly define LM for the context of this research. LM is defined using combination of definitions by prominent and commonly cited literature in the field (Shah and Ward, 2003; Holweg, 2007; Womack and Jones, 2013). For the context of this research, LM is defined as an approach that combines of sets of interconnected principles with aid of practices and tools to create upmost customer value through elimination of waste. This research considers both philosophical and practical approaches identified as well as human aspects. This definition is further clarified in the following section.

2.2.2. Lean Manufacturing Framework

The basis of Lean Manufacturing framework is derived from House of Lean created by Ohno (Liker, 2020) and represented in Figure 2.1. The framework is in shape of a house, with the roof representing the goal of LM and each element in the framework represents a LM principle that holds the roof and structure together. The components of the structure are interlinked, so that the strength of the whole system depends on the efficiency of each pillar and foundation of the house. The ideal concept of LM involves creating a comprehensive system that incorporates these principles, rather than implementing them individually and in isolation (Lander and Liker, 2007). Principles are accompanied by tools that help adoption of the principle (Bicheno and Holweg, 2016).

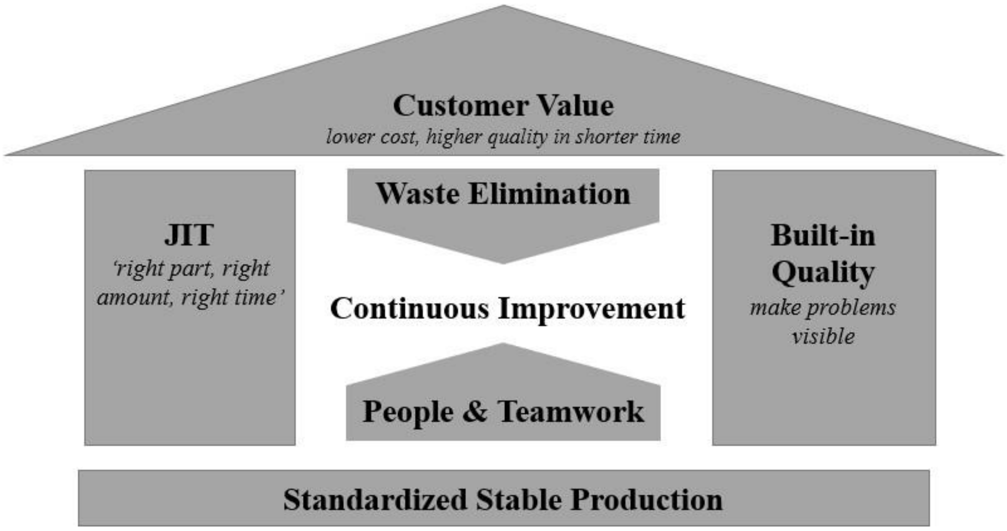


Figure 2.1 LM Framework adapted from Rüttimann and Stöckli (2016)

At the roof of the house lies the customer value where in the context of LM, value can be described as the price the customer is willing to pay for a product (Lyu, Chen and Huang, 2020). In practical terms, increasing value translates to higher quality, lower cost and shorter lead time. LM pursues perfection where strive to add customer value is a continuous never-ending process (Womack and Jones, 2013). The two pillars are Pull Production and Built-in Quality, with People & Teamwork at the centre, reflecting Ohno's human-centred approach (Ohno, 1988), where individuals drive Continuous Improvement and Waste Elimination. The foundation of this structure is built on Standardized Work. Each principle included in the framework will be explained below.

2.2.3. Elimination of Waste

At the core of LM is the principle of elimination of waste or non-value adding activities. A process adds value when it involves physical or information transformation that brings the product closer to what customer wants (Liker, 2020). The activities that do not transform the product are considered a non-value adding activity or a waste. As the existence of these activities deplete the resources from the company, it is essential to identify and eliminate them. These non-value adding activities are identified as transport, excess inventory, unnecessary movement of people, unused talent, waiting, overprocessing, overproduction and defects (Lyu, Chen and Huang, 2020) as shown in Table 2.1. While the original framework only included these 5 types of waste, unused talent was added later.

Type of Waste	Explanation
Transportation	Product's movement around the workstations or to any another location.
Inventory	Having excess inventory.
Motion	Unnecessary motion concerning employees across the stations including movements such as stretching or bending to get an item.
Waiting	Waiting in between processes.
Overprocessing	Creating a product that exceeds customer's requirement.
Overproduction	Producing more than needed.
Defect	Defects, reworks, scraps, and delays create unnecessary cost and waste of material.
Unused Talent	Unused human potential

Table 0.1 Description of Wastes adapted from Liker (2020)

Womac and Jones' (2013) framework outlines the stages of waste elimination, which start with identifying value and mapping the value stream. In this context, value is determined by the customer and generated by the manufacturer. Once the value is identified, the process of value stream mapping (VSM) commences. The activities involving waste elimination is done after VSM, where Value Streams can be visualised. VSMs display the information and material flow (Lacerda, Xambre and Alvelos, 2016) and the current state of the process can be displayed and by this visualisation wastes in the system can be identified. A desired future state can be created along with a plan of to achieve it with the aim of eliminating the waste (Tyagi and Vadrevu, 2015). In VSM, production variables such as cycle-time, transportation time are created to display current state. After creation of current state VSM, combination of LM principles can be used to make the processes flow and establish pull production (Rother, Shook and Institute, 2003).

VSM has been extensively integrated with technology, while the original process involved pen and paper; however recently new software has developed such as simulation (Helleno *et al.*, 2015; Meudt *et al.*, 2016). In addition to VSM's use with digital technologies, waste elimination principle has been mentioned broadly as a predecessor for digital technologies such as automation (Bortolotti and Romano, 2012). In this context, removing waste within a process is crucial, as digitizing a wasteful process would essentially perpetuate that inefficiency. As Bill Gates highlighted that automating an inefficient process would only worsen its inefficiencies, emphasizing that applying DT technologies without prior optimization can amplify inefficiencies (Bortolotti, Romano and Nicoletti, 2010; Chiarini and Kumar, 2020).

2.2.4. Built-in Quality

Built-in quality means integrating quality into the manufacturing process where the quality issues are visible and addressed through the products lifecycle (Järvenpää and Lanz, 2020). This involves ensuring immediate responses to address any issues, including stopping production if necessary to tackle quality issues as they arise (Bicheno and Holweg, 2016; Romero *et al.*, 2019). It also emphasizes visualising quality problems and training employees to avoid producing, passing on, or accepting substandard work (Kim, 2015). An essential aspect of built-in quality involves addressing quality issues, and one of the tools introduced by Taiichi Ohno that remains central to Lean Manufacturing is the Ishikawa diagram, also known as the fishbone diagram (Lanati, 2018). In fishbone diagram, to address the issues, employees look at the problem looking 6 aspects that are manpower, materials, methods, machines, measurement, and environment (Bicheno and Holweg, 2016). Through fishbone diagrams, employees improve process understanding, facilitate learning, manage negative factors, and identify the need for technical documentation (Botezatu *et al.*, 2019). They are also integral part of problem solving in Industry 4.0 context and its being integrated to software and smart devices (Coccia, 2020; Vo *et al.*, 2020).

Over the years, the built-in quality approach, combined with LM principles, has been enhanced by utilizing charts on the shop floor, enabling employees to effectively monitor and address issues, ensuring problems are visible and accountable (Parry and Turner, 2006; Berk and Toy, 2009). Today, many companies are integrating this principle with DT technologies by using tools such as touch screens to display live information and charts on the shop floor (Torres, Pimentel and Duarte, 2020; Tarantino, 2022). A recent study showcased another integration of Digital Transformation by implementing augmented reality (AR) on the shop floor, which offered operators real-time visualization and feedback for quality control, resulting in a 36% improvement in process time and a decrease in human errors (Alves *et al.*, 2021).

2.2.5. Just-in-Time

One of the pillars of LM is Just-in-Time (JIT) where products and materials in the value chain that are ready for the process ahead just-in-time that they are needed (Khalfallah and Lakhal, 2021). JIT can be achieved through Pull Production, where customer pulls the items are pulled from the downstream process in its own rate when needed, rather than the conventional method of pushing through a batch of items in front of the process. To facilitate pull production, Kanban was developed by Tachi Ohno as a tool that signals the previous process that more is needed (Liker, 2003). Through pull production and Kanban, production is matched to customers rate of demand to avoid overproduction and unnecessary inventory (Bicheno and Holweg, 2016). Flow focuses on the movement items across processes from start of production to the end. Creating a flow can be described as broad range of actions to get value rather than a set of tools (Holweg, 2007).

Kanban is a Japanese term translates to ‘card’ or ‘visual signal’. In TYP, it was a tool to assure just-in-time production (Ohno, 1988). Although there are variations of Kanban cards, in product form they serve as a visual presentation of an item on the production line. Originally, these cards were placed on a Kanban board where processes are marked. Each Kanban card is placed on belonging process and as the item goes through production it is passed along the board (Bicheno and Holweg, 2016). When the process finishes, the blank empty process and movement acted as a pull signal to the previous process to communicate that a new item is needed. The use of Kanban has become more complex adapting to different product systems and integrated with technology where some companies now use electronic Kanban systems (e-Kanban) (Phumchusri and Panyavai, 2015; Pekarčíková, Trebuňa and Kliment, 2019; Trebuna *et al.*, 2023). It has been adapted to complex systems for non-standard production schedules. Over time Kanban has developed more than a workflow management tool. It has been adapted with advancements in technology and software, making it a versatile method now used extensively in project management, personal productivity, and various other fields (Ahmad, Markkula and Oivo, 2013).

2.2.6. Standardised Work

Standardisation emphasizes the importance of setting standards, so a given task is performed in defined procedures, with defined set of tools, in the same sequence to give expected repeatable results (Medyński *et al.*, 2023). For standardisation, tools such as Standard Operating Procedures (SOPs) are used which guide operators on how to perform specific tasks and include details such as the purpose of the operation, required equipment and materials, setup, and operation procedures to ensure that all workers perform tasks uniformly, which is crucial for achieving consistent output (Akyar, 2012). It also helps it helps clarification each employee's job, enhances production effectiveness by providing clear instructions for each stage of the process, and establish product quality standards to ensure consistent quality (Sulistiyowati, Adamy and Jakaria, 2019).

Standardized work is also an important element unlocking application of digital technologies, such as robotics. As it involves the processes of establishing, formulating, and issuing standards, and then implementing them (Akyar, 2012). This is supported by a study that distributed a questionnaire to manufacturing professionals and revealed that 32% respondents confirmed that for facilitation of robotics was through standardized work (Marinelli *et al.*, 2021). A recent study used standardisation to assist in digitising LM principles (Medyński *et al.*, 2023). Therefore, the standardisation process that aids digitisation also highlights that standardisation is a dynamic system, necessitating individuals to understand what they are doing, why they are doing it and improve it over time (Bicheno and Holweg, 2016).

2.2.7. Continuous Improvement

Continuous improvement is an ongoing pursuit of seeking improvements and an ongoing cycle and aimed to be integrated into daily operations rather than treated as a separate activity (Sanchez and Blanco, 2014). The foundations of continuous improvement were made in TYP and still often referred as 'Kaizen' which is the Japanese word for 'continuous improvement' (Ohno, 1988; Lakshman, Kannan and Bhojraj, 2011). According to Tachii Ohno (1988), there is always something to be improved and reach for perfection is never-ending. Through kaizen, small improvements are made to provide greater benefits. With developments in operational management and quality, especially with the Deming's, Kaizen got integrated to different manufacturing processes (Villar-Fidalgo, Espinosa Escudero and Domínguez Somonte, 2019). For example, the concept of Kaizen workshops/sprint are developed as activities in companies to systematically analyse a process or a problem to seek solutions and it is done in cross-functional groups and involves a preparation and follow-up stage. Like other tools like Kanban, the use of Kaizen events went beyond manufacturing to healthcare and government (Ishak, Johari and Dolah, 2018).

Another method of ongoing improvement is through visual management where information is made visually available, so it is easily understandable to everyone (Parry and Turner, 2006). Further, visual process or work orders are made to help understand the situation further (Kurpjuweit *et al.*, 2019). In LM, visual management is used for many purposes, but it is an important tool for continuous improvement as it enhances information flow in organizations in forms of KPI tracking, quality and process flow (Eaidgah Torghabehi *et al.*, 2016). As a result, it is linked to not only continuous improvement but performance managements. Further, improvement activities can be displayed in scoreboards to track the progress of activities, employee performance and other KPIs (Suzaki, 1993).

Continuous improvement is integrated with DT technologies via digital boards that display live information, production goals, and KPIs (Müller, Alexandi and Metternich, 2020). Furthermore, the paper by Hiekata, Moser and Inoue (2019) emphasizes the significance of visual management in continuous improvement, digitized boards facilitate a common understanding by displaying clear, easy-to-read information, setting directions, guiding improvement activities, and empowering communication and knowledge sharing across various functional boundaries. This simplicity is crucial, as it integrates continuous improvement into daily operations which is important to ensure that the cycle of improvement remains active and effective (Sanchez and Blanco, 2014).

2.2.8. People & Teamwork

Employees have a crucial part in manufacturing and are at the heart of the LM according to TPS (Liker, 2020). One of the crucial elements is respecting employees and making sure that the manufacturing processes are tailored to their requirements, especially in new processes. The importance of the human aspect in technology integration was recognized early on when Toyota introduced the first mechanical automation process, which involved employee participation and was referred to as 'automation with a human touch.' (Yilmaz *et al.*, 2022). Furthermore, respecting involves getting them involved in the job and in this respect trusting people authority and developing them as problem-solvers (Coetzee, van Dyk and van der Merwe, 2019).

Respecting people is key for them to get involved in the manufacturing process for new processes. It also includes engaging people with the job, trusting them to solve problems and listening their suggestions (Ballé *et al.*, 2014) As employees know process best, they are in the best place to offer suggestions that could improve the efficiency and eliminate barriers, so when they are not valued think their suggestions are not being heard, this can cause companies to lose on improvement opportunities (Coetzee, van Dyk and van der Merwe, 2019). Hence, getting them involved in the job is crucial not only for enhancing existing processes but also for successfully implementing new processes.

Other than respect for people and involved employees, teamwork, more specifically cross-functional teams are considered a crucial element for LM applications (De Vries and Van der Poll, 2018). Cross-functional teams are focused on involving employees not only from manufacturing but also from various departments like design, finance, and marketing and allowing them to contribute to different aspects and insights (Karlsson and Åhlström, 1996). In manufacturing context, research has shown that good functioning cross-functional teams consisting of upper management, managers and shopfloor employees leads to success of LM applications (De Vries and Van der Poll, 2018).

The human element has been closely integrated with digital technologies, and the next industrial revolution is increasingly focusing on being human-centric as one of its key features for manufacturing operations (Nahavandi, 2019). More specifically, it aims to prioritize human well-being within manufacturing systems, achieving social objectives beyond mere employment and growth (Leng *et al.*, 2022). Supporting this Lean Manufacturing principle, advanced technologies such as collaborative robots handle repetitive and dangerous tasks, enabling humans to focus on creativity and efficient solutions, which enhances business productivity by motivating employees to perform their work (Adel, 2022).

2.2.9. Lean Manufacturing Principles in SMEs and Developing Countries

LM foundations were established in the large enterprise in developed country that is Toyota in Japan, which drew inspiration from another major manufacturer, Ford in US, when developing the Toyota Production System (TPS) (Liker, 2020). As a result, in early years, a lot of studies explored LM without considering a company's size, while others predominantly concentrate on large enterprises rather than SMEs (Belhadi *et al.*, 2018). Initially, there have been questions in academia whether LM principles are applicable in SMEs while research shows that they are indeed applicable, but SME characteristics need to be considered (Hu *et al.*, 2015). These SME characteristics are related to ownership, organizational structure, corporate culture, operational processes, human resources, and customer base (Elkhairi, Fedouaki and Alami, 2019). Considering the different structures have different effects, while SMEs have more central decision making and often simpler planning and control systems, but they lack resources, expertise and strategic perspective that larger enterprises have (Yadav *et al.*, 2019).

2.2.9.1 Success Factors and Barriers to LM in SMEs in Developing Countries

When it comes to application of LM principles, SMEs in both developed and developing countries face difficulties and experience similar barriers such as resource limitation (Maware, Okwu and Adetunji, 2022). To properly assess the impact of LM principles in SMEs, recent studies have focused on the adoption of LM principles specifically within SMEs, investigating the critical success factors and barriers. The most notable recent studies are summarised in the Table 2.2 below.

Summary	Reference
This research identified 48 critical success factors for adoption of LM principles in SMEs through analytical hierarchy process.	(Belhadi *et al.*, 2018)
Two SMEs are taken as case studies to examine LM principles, where critical success factors are identified.	(Pearce, Pons and Neitzert, 2018)
The study examines SME characteristics along with barriers and critical success factors application of LM principles in SMEs.	(Elkhairi, Fedouaki and Alami, 2019)
The literature review focuses on adoption of LM in SMEs, critical success fact applicability of LM in SMEs.	(Yadav *et al.*, 2019)
The research examines barriers to adoption of LM principles in SMEs and found that lack of understanding of principles, absence of sustainable implementation and lack of quality policy are amongst the most significant barriers.	(Qureshi *et al.*, 2022)
The study analyses responses from 350 participants from Indian SMEs to identify barriers to implementing Green LM principles. Key barriers include a lack of leadership support and inadequate employee involvement.	(Mohan, Kaswan and Rathi, 2024)
The research focuses on Mexican SMEs, examining financial performance and the application of LM principles. It identifies key barriers related to both technical challenges and human factors, particularly among employees.	(Guzmán, 2024)

Table 1.2 Summary of literature focusing on adoption of LM principles in SMEs

Shown in Table 2.2, literature focused on various aspects of LM principles in SMEs, ranging from critical success factors, barriers, and failure points. In SME context, the barriers of LM adoption were related to resistance to change, limited resources and fragmented and short-sighted strategy (Pearce, Pons and Neitzert, 2018; Qureshi *et al.*, 2022). In the context of SMEs in developing countries like Mexico and India, case studies reveal similar findings, highlighting resistance to change, along with limited skills and resources, as significant barriers (Panizzolo *et al.*, 2012; Guzmán, 2024; Mohan, Kaswan and Rathi, 2024). The critical success factors on the other hand focused on employee involvement, leadership support, clear objectives and communication (Hu *et al.*, 2015; Belhadi *et al.*, 2018; Yadav *et al.*, 2019). There has also been research focusing on which LM principles are amongst the most popular SME, which revealed that waste elimination along with VSM, Teamwork, JIT, and work standardization are some of the most frequently mentioned LM principles and tools (Zhou, 2016; Antosz and Stadnicka, 2017; Belhadi *et al.*, 2018).

2.2.9.2 Case Studies of LM Principles in SMEs in Developing Countries

After focusing on aspects such as barriers and success factors for SMEs, it is important to acknowledge various case studies demonstrating benefits of LM principles and applications in developing countries. According to Maware, Okwu, and Adetunji (2022), while there are some similarities, specific challenges and drivers differ when comparing developing countries to developed ones. However, one similarity is that application of LM principles benefits the manufacturing companies regardless of the location. For instance, in a recent study in a Peruvian textile SME, the use of tools and principles such as VSM and standard work improved quality by reducing reprocessing from 13.12% to 4.23% and increased productivity (Alanya *et al.*, 2020). A more recent study by (Ravalji *et al.*, 2023) examined LM principles in an Indian SME, discovering that eliminating waste through Value Stream Mapping (VSM) and implementing Just-In-Time (JIT) production via Kanban reduced robot assembly time by 37.12%.

Furthermore, benefits and awareness of LM principles has been present in some developing countries SMEs as even in an early study in India, research had 4 case studies that applied LM principles that showed operational performance benefits such as reduction of lead-time and improved quality (Panizzolo *et al.*, 2012). However, awareness of LM in developing countries has yielded mixed results. For example, Malaysian companies exhibited limited awareness (Adzrie and Armi, 2021) and similarly, Tanzania, a low-income developing country, showed limited awareness of LM principles, attributing it to resource constraints (Sinkamba, Matindana and Mgwatu, 2023). As the study by Maware, Okwu and Adetunji (2022) shows that differences exist between developed and developing countries regarding LM adoption there are also variations among developing countries themselves, highlighting the need for country-specific analyses.

2.2.10 Lean Manufacturing in SMEs in Turkey

In Turkey, manufacturing SMEs have good level of awareness of LM principles according to the studies conducted over the years. Even at a decade ago, a survey conducted by Iris and Cebeci (2014) revelead that among the 53 manufacturing Turkish SMEs, there is a strong initiation of LM principles, although they encounter challenges when it comes to putting them into practice. A recent research study in Gaziantep, a significant manufacturing hub in Turkey, revealed that most companies in the area exhibited a moderate to high level of awareness and implementation of LM principles within their organizations (Gelmez *et al.*, 2020). This is further corroborated by case studies conducted. For instance, research done on micro enterprises in Turkey, showed that LM principles addressed various operational problems such as low productivity and disorganized shop floors (Inan *et al.*, 2022). In another case study, LM principles extended beyond merely enhancing operational performance to improving sustainability within solar energy firms in Turkey which included applying Lean's pull and flow principles to achieve both economic and social dimensions of sustainability (Aldewachi and Ayağ, 2022).

The adoption of LM principles on SMEs dates to 1980-2000s (İşler, 2000). The first case studies focusing on flow focusing on was published during that period along with a guideline on how to adopt JIT in Turkish manufacturing SMEs (Doyuran, 1990; Soyuer, 1999). Over the last two decades, Turkey has made significant steps in terms of adoption of LM principles in SMEs through support a public institution called KOSGEB (Küçük ve Orta Ölçekli İşletmeleri Geliştirme ve Destekleme İdaresi Başkanlığı) which translates to Small and Medium Enterprises Development Organization. KOSGEB was established in 1990 as part of Turkish Ministry of Industry and Technology, also called as STB, to support and aid efficiency of SMEs in Turkey (CBFO, 2023). It aims to enhance competitiveness and market share of SMEs, through providing guidance, consultancy and training (Bulak *et al.*, 2016). KOSGEB also provides funding to SMEs and assists entrepreneurs in establishing and managing their businesses (Başçı and Alkan, 2015). The financial support may be either non-refundable or refundable, depending on the program, and includes options such as lean manufacturing, digital transformation, green industry, energy efficiency, and R&D support (KOSGEB, 2024a).

In recent years, one of the primary focus areas of KOSGEB in manufacturing is centred on encouraging SMEs to adopt LM principles where it provides various services including training, advisory and workshops. In 2023, a ‘Lean Transformation’ program was launched, featuring 30 introductory meetings held in 26 different cities across Turkey to promote the initiative (Turkish Ministry of Industry and Technology, 2023a). Furthermore, KOSGEB’s advisory programme includes a Lean Maturity Assessment Tool, where SMEs can measure and improve their progress through adopting LM principles on completion of this assessment, SMEs are qualified for a funding worth 10.000 Turkish liras (KOSGEB, 2023b). When assessments reveal the need for additional support in adopting certain LM principles, training is provided at Model Factories, which are centers for training and competence development. According to the Turkish Ministry of Industry and Technology (2023) these centres primarily aim to help manufacturing SMEs enhance their efficiency through Lean Manufacturing and Digital Transformation in a scalable and experimental way.

Model Factory initiative was launched by Turkish Ministry of Industry and Technology and United Nations Development Programme (UNDP) in 2015. Initially 8 model factories were built in prominent Turkish cities renowned for their substantial manufacturing communities and towards the end of 2023, a total of 14 model factories are aimed to be operational (Albayrak, 2023). Model Factories have 14 different trainings focusing on specific LM principles and tools which they offer after the Lean Maturity Assessment. KOSGEB encourages SMEs to attend LM trainings in Model Factories through series of funding support. For each training they get on LM principle such as continuous improvement, waste elimination or VSM, SMEs get a non-refundable funding of 5000 Turkish liras, where the total amount could go up to 70.000 Turkish liras (KOSGEB, 2023b).

In summary, manufacturing SMEs in Turkey have awareness to LM principles (Iris and Cebeci, 2014; Gelmez *et al.*, 2020) and receive a strong support and encouragement from KOSGEB, the government institution supporting SMEs, in forms of funding, advisory and training (Bulak *et al.*, 2016). This support includes offering advisory services, periodically using the Lean Maturity Assessment tool to monitor progress, and facilitating access to training opportunities, particularly in the context of Model Factories, to enhance SMEs' capabilities in this regard (Albayrak, 2023; KOSGEB, 2023b).

2.3 Digital Transformation Technologies

2.3.1 Definition of DT and its technologies

Digital Transformation is a combination of two words that are ‘digital and ‘transformation’. The word digital refers to transfer from analog work to digital, where composited systems use 0 and 1 coding (Merriam-Webster, 2024). Transformation refers to an act of changing from one to another and in very simple terms DT is transferring a company’s operations from digital (Romero *et al.*, 2019; Bittencourt, Alves and Leão, 2020; Demeter, Losonci and Nagy, 2020). According to Hess *et al.* (2016) the companies that go through DT goes through certain steps. Firstly, a company incorporates digital technologies that align with the firm's strategy, leading to value creation during the process of digital transformation. Structural modifications are made in areas such as processes and employees, while the presence of financial pressures acts as a driving force behind the push for digital transformation.

While the roadmap to DT has been unclear for many companies particularly SMEs (Appio *et al.*, 2024), there has been frameworks that define the technologies part of DT. In manufacturing context, digital or smart factories stand as the ultimate aspiration of Digital Transformation (DT), incorporating diverse technologies in manufacturing plants with the overarching aim of creating value (Sufian *et al.*, 2021; Sahoo and Lo, 2022). More specifically, a digital factory imagines a complete system in which computer-aided tools, spanning product planning to factory operations, are linked via a central database (Bracht and Masurat, 2005). In the initial stages, the concept of the digital factory was introduced; however, with the advent of Industry 4.0, the focus has shifted towards smart factories where these advanced facilities aim to operate with real-time data, facilitating seamless exchange between machines and enabling data analysis for informed decision-making (Shariatzadeh *et al.*, 2016).

Industry 4.0 have been used interchangeably with DT in manufacturing in the academia (Prinz, Kreggenfeld and Kuhlenkötter, 2018). After adoption of digital technologies in 3rd Industrial revolution, the Fourth Industrial Revolution (often referred to as Industry 4.0) focuses the integration of digital technologies with physical systems, enabling communication between them (Lasi *et al.*, 2014). This integration, coupled with data analysis, facilitates automated decision-making processes with advanced real-time data collection and processing, hence the word ‘smart’ was derived (Zheng *et al.*, 2018). While Industry 4.0 is mostly focuses on manufacturing operations (Lasi *et al.*, 2014), DT has a broader vision that includes business strategy, human aspects and organisational related outcomes (Matt, Hess and Benlian, 2015). DT includes not only manufacturing operations targeted by Industry 4.0 but also extends to human-centric and financial domains. As a result, the research incorporates literature related to Industry 4.0 within its scope.

A framework was developed by Ghobakhloo and Iranmanesh (2021) to describe DT in Industry 4.0 era through digital technologies incorporated in smart factory in SMEs. These technologies are categorized into six areas, which include Simulation and Digital Twin, Big Data Analytics, Cyber-Physical Systems (CPS), Automation and Robotics, Cloud Computing, Augmented Reality, Advanced Manufacturing, and the Internet of Things (IoT). The technologies such as Internet of Services, Blockchain and Cybersecurity focused on elements outside the organisation and are not included due to the scope of the research as intercompany. For example, Internet-of-Services focuses on customer engagement and monitoring which is outside the organisation and out of the scope of this research. The definitions of these digital technologies are displayed in the Table 2.3 below, which will be supported in SME context further in the section.

DT technologies	**Definitions**
Simulations and Digital Twin	Simulations are used to imitate real life physical processes or systems often through computer systems (Bai *et al.*, 2020). Digital Twin relates to having a virtual representation of products or processes without having need to access it (Pérez *et al.*, 2020).
Big Data Analytics	Big Data Analytics includes analysis large volume of data with the goal of revealing insights and extracting meaningful information (Bai *et al.*, 2020).
Cyber Physical Systems (CPS)	Cyber-physical systems include physical identities such as robotics to be connected through a virtual network to exchange live information and initiating actions (Dalmarco *et al.*, 2019).

Automation & Robotics	Robotics involves use of robots for tasks, whereas automation focuses the utilization of mechanized technology for automatic operations. Automation and robotics enable the elimination of humans from tasks that are hazardous and physically demanding (Jagtap *et al.*, 2020).
Cloud Computing	Cloud computing allows storage of data and access to IT services through a cloud platform (Wu *et al.*, 2010; Bai *et al.*, 2020).
Internet-of-Things (IoT)	It means the interconnection of physical items through internet by sensors, actuators, and additional gadgets capable of gathering and transmitting data concerning these items (Mallieswari and Aravinda Reddy, 2019).
Advanced/Additive Manufacturing	A manufacturing process of creating parts/objects in layers through 3D model in a flexible and customisable way (Ahmed, Jeon and Piccialli, 2022).
Artificial Intelligence	Artificial Intelligence aims to focuses on developing smart machines capable of functioning and responding in a human-like manner (Bai *et al.*, 2020).

Table 2.3 Digital Technologies included in this study and their definitions

2.3.2 Integration and Applications of DT Technologies into SMEs

While the technologies that drive DT are categorised, it is important to understand how their integrations impact on the companies, especially SMEs. The impact can be described by the framework by Haghnegahdar, Joshi and Dahotre (2022) where it highlights those digital technologies have an impact on value creation and value offer mechanisms of SMEs as displayed Table 2.4. Value creation is described as the series processes that the company undergoes to provide the customer with the product. For instance, incorporating robots or automation to a manufacturing process changes how products are made, thus affecting the way value is created. Value creation can be characterized as a process-centric focus, where DT technologies such as robotics centres on the processes responsible for delivering value to the customer (Puica, 2022). Furthermore, value offer is what the company offers to the customer, which is in this context it refers to the products that are manufactured (Müller, Kiel and Voigt, 2018). For example, advanced simulations and virtual 3D models are used with the purpose to enhance the products, where engine parts that are simulated in 3D models provide better performance to the customer. This can also be termed a product-centric, as it generates value by improving the value offerings of the product.

Impact on Value	Focus	Meaning in Context	Examples
Value Creation	Process-Oriented	Focuses on the changes on the process and elements involving how products are created	Automated production, machine monitoring, technology-based training for staff
Value Offer	Product-Oriented	Focuses on the change of value offered by a product, in terms of developments and enhancement related to products and its performance.	Larger product spectrum, more flexible products

Table 2.4 Impact of digital technologies to SMEs

The literature on Digital Transformation (DT) is grouped by digital technologies, which will be categorized based on their impact on Small and Medium-sized Enterprises (SMEs) business models according to Table 2.4. A literature review of the elements used in the SME context are shown below:

DT Technology	Impact on Business	Details of use of DT technologies	References
Simulations and Digital Twin	Process	Use of simulations for process development and optimization.	(Kuts *et al.*, 2019; Trebuna, Pekarcikova and Edl, 2019; Florescu and Barabas, 2020; Guo *et al.*, 2021; Xia *et al.*, 2021)
	Product	Use of Digital Twin / virtual model for product representation and development.	(Zheng, Yang and Cheng, 2019; Park, Woo and Choi, 2020; Zhang *et al.*, 2020; Gandouzi *et al.*, 2022)
Big Data Analytics	Product	Use of Big Data Analytics for product development.	(Tan and Zhan, 2017; Jagtap *et al.*, 2020; Tsang *et al.*, 2022)
Cyber-physical Systems (CPS)	Process	Monitoring the production process in real-time	(Canizo *et al.*, 2019; Lee and Kundu, 2022; Napoleone *et al.*, 2023; Ryalat, ElMoaqet and AlFaouri, 2023)
Automation & Robotics	Process	Use of Automation in manufacturing processes	(Lu, Xu and Wang, 2020; Siderska, 2020; Lievano-Martínez *et al.*, 2022; Schlegel and Kraus, 2023)
	Process	Use of robotics in manufacturing processes	(Matheson *et al.*, 2019; Stadnicka and Antonelli, 2019; Barosz, Gołda and Kampa,

			2020; Evjemo *et al.*, 2020; Xu *et al.*, 2021; Pillai *et al.*, 2022)
Cloud Computing	Process	Use of cloud computing to store and access production	(Ghomi, Rahmani and Qader, 2019; Qi and Tao, 2019; Liu *et al.*, 2022)
Internet of Things (IoT)	Process	Connection of machinery and devices through sensors and other devices to communicate with each other and receive feedback.	(Saqlain *et al.*, 2019; Kalsoom *et al.*, 2021; Haghnegahdar, Joshi and Dahotre, 2022)
Additive/Advance Manufacturing	Product and Process	Use of additive manufacturing / 3D printing	(Mehrpouya *et al.*, 2019; Godina *et al.*, 2020; Ashima *et al.*, 2021; Parmar *et al.*, 2022)
Artificial Intelligence	Process	Use artificial intelligence in terms of predictive maintenance machine learning	(Lu, Xu and Wang, 2020; Siderska, 2020; Lievano-Martínez *et al.*, 2022; Schlegel and Kraus, 2023)

Table 2.5 Overview of recent literature on digital technologies part of DT

The DT technologies described on Table 2.5 will be explained in detail, also giving examples of their use in SME context. Starting with Digital Twin which is defined as a virtual counter part of a physical identity in manufacturing. It is often defined synonymously to a virtual 3D model (Singh *et al.*, 2021) or an enhanced multi-scale simulation that reflect reality (Shafto *et al.*, 2012). Digital Twin has connections to physical realm and a digital environment, along with an information processing layer that serves as the bridge between the two (Zheng, Yang and Cheng, 2019). A popular area of study for Digital Twin in manufacturing sector focused on products development aspect with product-orientation, where a virtual model is used for developments related to product design and its life cycle (Tao *et al.*, 2019; Zheng, Yang and Cheng, 2019; Lim, Zheng and Chen, 2020). In SME context, studies are ongoing where a recent study on SMEs and digitalization has introduced a versatile process-technology-performance matrix for digital twin-based engineering, which SMEs can implement to enhance product development and improvement (Dutta and Kumar, 2024).

Further, the emergence of the word Digital Twin was in 2002 on a presentation related to product life cycle management (Pires *et al.*, 2019). Beyond developing a virtual model another digital technology associated with Digital Twin is simulations (Kuts *et al.*, 2019; Florescu and Barabas, 2020; Guo *et al.*, 2021; Xia *et al.*, 2021). Simulations are not a new technology, their application in manufacturing dates to the 1950s (Gunal, 2019). However, their utilization has expanded and diversified over time where simulations have a process-focus also used for modelling and optimising a manufacturing processes and layouts in SMEs (Sony *et al.*, 2022). In some applications whole manufacturing systems are simulated to design, optimise, and improve the process layouts (Trebuna, Pekarcikova and Edl, 2019). Further in SMEs, simulation is employed to tackle quality problems in processes and to redesign production workflows to reduce lead times (Soundararajan and Reddy, 2020; Ondov *et al.*, 2022) (Soundararajan and Reddy, 2020; Ondov *et al.*, 2022) Additionally, it is utilized for process development and the integration in an Italian SME (Frecassetti *et al.*, 2023).

As another DT technology, big data analytics can help understand how the product is being used, its life cycle and areas of improvement (Wilberg *et al.*, 2017). Big data allows capturing and analysing the needs of customer where companies can create opportunities to shape their products according to customers preference (Zhan *et al.*, 2018). Once customer preferences and market trends are captured, this data can be connecting it to design parameters to enhance the existing products (Tsang *et al.*, 2022). Beyond enhancing existing products, big data analytics is increasingly being utilized for new product development, and while studies are limited, it has been shown to assist the early design stages, shorten the design cycle, and support decision-making (Ali, Helgesen and Falk, 2021). Similarly, a study demonstrated that using big data analytics in an electronics company, guided by the principles of autonomy, connectivity, and ecosystem, can accelerate and reduce the cost of new product development (Tan and Zhan, 2017). In SME context, a study explored the utilization of big data analytics for product design and enhancement from the viewpoint of SMEs and concluded that SMEs have data and use them in various ways, including for improving their products and services, although they can be used more effectively (Liu *et al.*, 2020). The used of big data leads to performance benefits in SMEs as a study conducted on manufacturing companies in a developing country demonstrated that data analytics positively influence sustainable product development, which subsequently improves organizational performance (Ali *et al.*, 2020).

Cyber-Physical Systems (CPS) are defined by the integration and coordination between computational and physical processes through networking, where devices with processing elements are connected to monitor, sense, and control real-world physical components (Park, Zheng and Liu, 2012). Furthermore, it refers to connectivity of physical and computational in a platform where one of the main aims is to monitor and show real-time progress (Canizo *et al.*, 2019). For SMEs, CPS can improve production efficiency and lower manufacturing costs, aiding competitiveness and innovation, but they frequently lack the financial and human resources and knowledge to develop CPS competencies and utilize available technologies (Jordan *et al.*, 2017). Despite challenges, CPS continues to be utilized in SMEs such as connecting customers with manufacturing companies, facilitating the rapid prototyping of temporary networks for personalized products (Saniuk and Grabowska, 2021). Further, in a more popular application SMEs involve adopting CPS to enable real-time information, collected through IoT, to feed different production improvement mechanisms like planning, scheduling, and monitoring (Ferreira *et al.*, 2020).

Automation and robotics have a process-orientation in terms of value as physically straining and repetitive processes carried out by human can be eliminated through automation and robots (Jagtap *et al.*, 2020). Automating production processes improves efficiency and often leads to higher quality outputs where robots are linked to improved performance and increased productivity (Ballestar *et al.*, 2020; Hypki *et al.*, 2023). They are relatively old technologies where its history dates back to the 1950s (Brock, 2012). In terms of robotics, advancements in robotics technology have led to the collaborative robots, known as cobots, that are actively trying to be used in SMEs (Yang *et al.*, 2023). Cobot is a user-friendly collaboration between robot and humans where cobots work with human in a robot-human shared shop floor and are often seen as a possible replacement for human employees (Pauliková, Babelová and Ubárová, 2021; Javaid, Haleem, Singh, Rab, *et al.*, 2022; Vido, Digiesi, *et al.*, 2024). Furthermore, to help integrating cobots in the SME manufacturing sector TU Delft in the Netherlands established the Cobot Learning Center (COLEAC) that train SME professionals (van Dam *et al.*, 2021). In terms of automation, beyond its application in robotics, its development is associated with lean manufacturing (Rossini, Powell and Kundu, 2022). Research associates LM principles with lean automation, particularly through the TPS, which emphasizes a human-centric approach (Yilmaz *et al.*, 2022). By advancing on this, current research highlights that lean automation by managing the interactions among social, technical, and operational factors aims for cost-efficiency, reliability, and simplicity (Vlachos *et al.*, 2023).

Cloud computing is a model that enables on-demand access to shared computing resources such as network and servers while cloud manufacturing extends this concept to provide on-demand access to manufacturing resources to display these to the stakeholders hence creating flexible production lines to improve efficiency and reduce costs (Wu *et al.*, 2013). The information accessed from cloud computing offering real-time information and creates a dynamic structure where important stakeholders machine owners, product designers, and customers can communicate and collaborate (Helo *et al.*, 2021). There has been an increase for use in manufacturing SMEs, where research done in Saudi Arabia revealed that SMEs have barriers such as security, privacy, and lack of guidance (Alsafi and Fan, 2020). Additionally, a recent literature review shows significant adoption, developing countries face considerable obstacles due to a lack of strategy, skilled workforce, and technology awareness (Kavre, Sunnapwar and Gardas, 2023). Despite the barriers, cloud computing is considered crucial for DT and intelligent manufacturing systems, covering the entire product life cycle and processes from design, production to maintenance, functioning as a parallel and intelligent network that manages production resources and capacities (Zhong *et al.*, 2017).

Although there is no universally accepted definition, the Internet of Things (IoT) typically describes the internet network connectivity and through that the extension of computing power to include to objects, sensors, and everyday items (Rose, Eldridge and Chapin, 2015). IoT applications in manufacturing companies include tracking devices that monitor shipments and equipment movement, providing real-time updates to optimize the supply chain and sensors offering insights into production equipment such as energy consumption (Soori, Arezoo and Dastres, 2023). Furthermore, together with cloud manufacturing, IoT and cloud computing is one of the most used DT technologies in SMEs primarily due to their low cost and ease of application, as highlighted in studies (Moeuf *et al.*, 2020; Hansen and Bøgh, 2021). There has been increased interest in low cost IoT systems in literature (Martikkala *et al.*, 2021; Sunny *et al.*, 2021). Advanced low-cost sensors and technologies are available to enable extensive data collection across various devices throughout manufacturing processes (Kalsoom *et al.*, 2021). These advancements in making these technologies low cost and simple are particularly important as SMEs are limited in their financial resources and often lack technical skills to adopt DT technologies (Mittal *et al.*, 2018).

Artificial Intelligence, simply put, involves creating machines that mimic human-like intelligence and behaviour (Simmons and Chappell, 1988; Ertel and Black, 2018). In terms of manufacturing context, AI improves efficiency through accelerating production process design, promoting collaborative product development, reducing quality control risks, and increasing transparency for both producers and customers (Huynh-The *et al.*, 2023). One key use of AI in manufacturing is predictive maintenance, which combines data collection from machines with AI analysis to optimize maintenance timing, improving system availability, reducing costs, and enhancing performance and safety (Cardoso and Ferreira, 2021). In recent years, numerous studies have examined AI-driven predictive maintenance specifically for SMEs providing insights on potential benefits, challenges, unique features, and best practices (Dolatabadi and Budinska, 2021; Khan *et al.*, 2022). AI-powered predictive maintenance in SMEs utilizes machine learning and deep learning methods to efficiently and accurately analyse machine data through multiple processing layers (Rastogi *et al.*, 2020). Through that, predictive maintenance enables early failure detection, minimizes machine downtime, and accurately predicts equipment lifespan (Keleko *et al.*, 2022).

Additive manufacturing has an impact on both how the value is created, and value offered, as in terms of product offering 3D printing has caused new components and products to be created through new shapes (Godina *et al.*, 2020). Furthermore, it facilitated the integration and advancement of composite materials, which, combined with adaptable design and manufacturing approaches, are used extensively in manufacturing including the aerospace components (Praveena *et al.*, 2022). With product-focus, 3D printing enabled a possibility of customised mass production (Mehrpouya *et al.*, 2019). In the SME context, 3D printing offers the platform and expertise to develop, test, and market new products, minimizing the necessary resources and enabling SMEs to undertake multiple product development projects with low initial investments cost (Walsh, Przychodzen and Przychodzen, 2017). Due to the opportunities and benefits attached, studies have focused the role of Additive manufacturing/3D printing in SMEs along barriers specific to SMEs focused on proposing solutions (Martinsuo and Luomaranta, 2018).

In summary, DT technologies have been incorporated into SMEs from Digital twin to additive manufacturing as explained in this section. Digital twins offer an improvement focusing on product and process aspects in SMEs, through providing virtual counterparts to physical entities in manufacturing and enabling process optimization through simulation (Tao *et al.*, 2019; Zheng, Yang and Cheng, 2019; Oliveira *et al.*, 2022). CPS uses computational and physical systems to provide real-time information and allow interaction between stakeholders in SMEs improving efficiency and reducing costs (Ferreira *et al.*, 2020). Further, automation and robotics, in forms of collaborative robots and lean automation in SMEs, eliminate repetitive tasks and enhance productivity (Tortorella *et al.*, 2020; Yang *et al.*, 2023). In SMEs, Cloud computing and IoT are one of the most popular DT technologies as they enable real-time data sharing, storage, and collaboration in a low-cost way (Moeuf *et al.*, 2020). Moreover, AI, particularly in predictive maintenance, optimizes machine data analysis to improve system availability and reduce costs (Dolatabadi and Budinska, 2021) . Lastly, additive manufacturing, or 3D printing, offers SMEs the ability to develop, products with low financing requirement and facilitates the way to customized mass production (Walsh, Przychodzen and Przychodzen, 2017; Mehrpouya *et al.*, 2019).

2.3.3 Digital Transformation and Operational Performance

The previous section detailed the integration and applications of DT technologies, highlighting their benefits for SMEs. The primary motivation for adopting DT technologies is the enhancement of operational performance, as demonstrated by numerous studies involving SMEs (Guo and Xu, 2021; Teng, Wu and Yang, 2022; Yu, Wang and Moon, 2022). Operational performance benefits of DT technologies can be grouped under inventory, lead-time, product quality, productivity, and cost according to recent notable literature shown in Table 2.6.

Operational Performance Area	**Improvement Focus**	**Reference**
Inventory	Reduced inventory	(Mashayekhy *et al.*, 2022; Panigrahi, Shrivastava and Nudurupati, 2024)
Productivity	Productivity improvement	(Canizo *et al.*, 2019; Calabrese *et al.*, 2020; Chauhan, Singh and Luthra, 2021; Fatorachian and Kazemi, 2021; Szász *et al.*, 2021)
Quality	Improved product quality	(Calabrese, Levialdi Ghiron and Tiburzi, 2021; Chauhan, Singh and Luthra, 2021; Szász *et al.*, 2021; Yu, Wang and Moon, 2022)

Cost	Reduced costs of production	(Calabrese, Levialdi Ghiron and Tiburzi, 2021; Chauhan, Singh and Luthra, 2021; Szász *et al.*, 2021; Yu, Wang and Moon, 2022)

Table 2.6 Summary of operational performance benefits of DT technologies

Benefits of DT technology have been recognised in SMEs through many studies as outlined in Table 2.6. Firstly, when it comes to inventory, DT technologies are used for management, optimisation and reduction (Panigrahi, Shrivastava and Nudurupati, 2024). One of the most significant technologies when it comes to inventory management is IoT, where the applications include tracking equipment and spare parts to enabled sensors help (Keivanpour and Kadi, 2019; Mashayekhy *et al.*, 2022). In support of this, simulation is used to optimise the inventory systems (Jeenanunta, Kongtarat and Buddhakulsomsiri, 2021). Focusing on effects of Industry 4.0, many studies have identified productivity improvement related to DT technologies on a broader scale (Calabrese *et al.*, 2020; Fatorachian and Kazemi, 2021). In a more specific example, displaying real-time information through CPS, allow early detection problems aiding productivity (Canizo *et al.*, 2019). Szász *et al.* (2021) conducted an extensive survey including 705 manufacturing plants to conclude that implementing digital technologies have improved operational performance in many areas one of the significant improvements being productivity, lead-time, and quality.

Focusing on lead-time improvement, the use of robotics and automation in manufacturing SMEs has shown to reduce lead times and increases flexibility (Zheng *et al.*, 2019). This is further supported by another technology that is additive manufacturing which can allow on shorter lead-times for custom products (Walsh, Przychodzen and Przychodzen, 2017, p. 20). Additionally, adopting DT technologies improves quality in manufacturing companies (Calabrese *et al.*, 2020; Szász *et al.*, 2021). For example, cloud manufacturing provides an integrated quality control system that enhances quality through improved detection and control (Ying *et al.*, 2021). Shifting to cost reduction, various DT technologies play a significant role; automation and robotics reduce labour costs (Menon and Shah, 2020; Koch, Manuylov and Smolka, 2021), while predictive maintenance lowers expenses by preventing equipment breakdowns (Keleko *et al.*, 2022). Supporting these findings, the study by Choi *et al.* (2022) highlighted the benefits of DT technologies such as IoT, robotics, and AI individually. Hence, as supported by relevant evidence and literature, DT technologies significantly enhance operational performance through various technological applications.

2.3.4 Digital Transformation in Turkish SMEs as a Developing Country

To explain the situation of DT in Turkish SMEs, this section will first analyse the overall literature on DT in Turkey, considering that SMEs are integral to this ecosystem. Following this, the focus will shift to specific literature concerning Turkish SMEs. The digital transformation in Turkey can be understood by examining the characteristics and features typical of a developing country. Supporting this research, when discussing developing countries, it is important to note that their broad scope and features vary from country to country, so findings are not representative of all developing countries (Karakaya, Alataş and Yılmaz, 2020). In line with this, a recent study by Yildirim *et al.* (2023) used text mining to analyse policy documents and scientific literature, clustering countries based on their national policies and contexts. The results placed Turkey in the same cluster as developing countries like Hungary. The following section examines Turkey's economy, income, labour, industrialization, and technology awareness and infrastructure, providing a foundational background for understanding digital transformation in Turkey and enabling comparisons with other developing countries. It ends status of digital transformation in Turkish SMEs supported by relevant literature and case studies.

2.3.4.1 Features of Turkey as a Developing Country

According to International Monetary Fund (IMF), Turkey listed as developing country and is world's 17th largest economy (IMF, 2023). Experiencing substantial growth between 2006 and 2017, Turkey's population income was elevated to upper-middle-income (The World Bank, 2024). However, Turkey's economy is still developing, with needed improvements in income distribution and poverty reduction, particularly pressing as the poverty rate rose to 14.4% in 2024 amid high inflation challenges (European Commission, 2023). When it comes to labour, Turkey has one of Europe's largest labour forces, ranking second with 34.3 million people, comprising both unskilled and skilled workers (CBYO, 2023). As another characteristic of a developing country, Turkey has relatively cheap labour compared to developed nations, with the minimum wage in 2024 being 578€ per month, which is on the higher end among developing countries (Saget, 2008; Yackley, 2023). In summary, when it comes to developing country characteristics, Turkey has an upper-middle-income status, but it still faces challenges in income distribution and poverty, and has a large, relatively cheap labour force.

After providing economical background of Turkey, the next important point to consider when it comes to DT in manufacturing is industrialisation and advance manufacturing ecosystem. Turkey is highly industrialised with manufacturing section is accounting for 22% of countries GDP (World Bank, 2023). Turkey's advanced manufacturing, led by international automotive and aviation firms with local suppliers, and industries like consumer goods, electronics, chemicals, and textiles, are increasingly adopting cutting-edge technologies (Akguner, 2024). Manufacturing in Turkey is supported through its strategic geographical location, high population, and skilled labour where it produces 900,000 university graduates annually that are equipped with technology awareness (CBYO, 2023; Bazaluk *et al.*, 2024). Further, the manufacturing ecosystem in Turkey is significantly influenced and led by major manufacturers like Ford, Renault, and Phillip Morris, as well as prominent Turkish manufacturers such as Arçelik, all of which have established production facilities in the country (Aksak and Duman, 2016). By establishing top-tier facilities, demanding high quality from their Turkish suppliers, and setting up smart factories, big companies like Bridgestone, in collaboration with Sabancı Holding, emphasize and support digital transformation among Turkish manufacturers (Vardar, 2020).

2.3.4.2 Digital Transformation Maturity in Turkey's Industrial Sector

In terms of DT awareness and readiness Turkish SME, a study has been completed with the aim of understanding current situation and offer improvement solutions (Gergin *et al.*, 2020). Another study conducted among 193 Turkish SMEs revealed that SMEs are currently utilizing sensor systems, automation, and preventive maintenance, but show lower familiarity with the Internet of Things (IoT) and additive (3D) manufacturing (Gergin *et al.*, 2019). Another recent study in Turkey focused on 105 SMEs to analyse barriers and adoption of DT technologies and revealed that manufacturing SMEs think that DT adoption increased customer satisfaction, helped fulfil their requirements but further commented that privacy and security concerns (Sırkıntılıoğlu and Durukan, 2023). The benefits gained by SMEs included increased productivity and demand, along with reduced costs, as significant benefits of digital transformation technologies (Gergin *et al.*, 2019). Furthermore, applications of DT technologies are frequent in Turkish SMEs. For instance, a case study focused on Digital Twin application in a Turkish manufacturing company to evaluate sustainability (Unal, Albayrak and Unal, 2023). Another study looked at applications of automation in a SME producing manufacturing lifting equipment (Karakus, Öztürk and Güldogan, 2021).

Focusing on Digital Transformation in Turkey, Turkey has a programme that evaluates its progress through Digital Transformation Index (DTI), where evaluation based on 10 pillars are made and 64 indicators

(TÜBİSAD, 2023). These pillars include environment in terms of political and business, digital readiness in terms of infrastructure, affordability, and skills, thirdly usage of technology and impact in terms of economic and social impact. Between 2019-2021 all four sub-indexes of Turkey's digitalization score showed positive improvements highlighting enhancements in DT while the 2022 data show stagnation (TÜBİSAD, 2022). The report showed that technological readiness demonstrated slow progress; although affordability improved, weak infrastructure and insufficient skills, particularly in STEM education and digital infrastructure (TÜBİSAD, 2023).

To address the barriers of DT such as insufficient skills and training, Turkish government have been supporting manufacturing companies, especially SMEs, through series of initiatives. The main way Turkish government supports SMEs through KOSGEB which is the public institution supporting SME development as mentioned in Section 2.2.10. There are Model Factories, also called Capability and Digital Transformation Centre, are established in various cities around Turkey to provide experimental learning and consultancy specifically for manufacturing SMEs (UNDP, 2019; Albayrak, 2023; Turkish Ministry of Industry and Technology, 2023a). In a most recent support, KOSGEB has released a scheme that allows financial support of up to 20 million liras to allow adoption of DT technologies such as AI, robotics and automation (KOSGEB, 2024a). In line with this, Turkey aims to invest 1-1.5 M $ annually for integration of DT technologies to manufacturing processes (Akguner, 2024).

In summary, DT in Turkish SMEs is explained by broader economic and industrial context. The industrialisation and significant influence from major manufacturers like Ford, Renault, Arçelik, Brisa (Aksak and Duman, 2016; Vardar, 2020), as well as initiatives like KOSGEB and Model Factories supporting digital transformation in Turkey (Sırkıntılıoğlu and Durukan, 2023; Turkish Ministry of Industry and Technology, 2023a). While many SMEs are utilizing DT technologies there are barriers to overcome where benefits include improved productivity and lower cost (Gergin *et al.*, 2019).

2.4 Lean Manufacturing and Digital Transformation

2.4.1 Integration of LM and DT

2.4.1.1 Empirical Studies Integrating LM and DT

Innovation and new technologies have always had a part in LM, since the start of TPS. In the late 1800s, the first mechanical automation concept in Toyota was invented by Sakichi Toyoda to relieve employees from labour-intensive work (Liker, 2020). As part of Built-in Quality principle, Ohno also developed automation by human touch, where employees would be part of the process and stop the automation and production when a defect is detected (Yilmaz *et al.*, 2022). Over time LM principles get more integrated with DT technologies and research has identified overall a synergetic relationship between LM and DT where notable research is shown in the Table 2.7 below.

To identify the relationship between LM and DT, specific LM principles and DT technologies are aimed to made link in research. Sanders *et al.* (2017) uses an interdependence matrix to show the relationship between Industry 4.0 and LM principles and identified overall a synergetic relationship. Additionally, in a subsequent study, an analysis of specific pairwise relationships between the industry technologies and LM principles were conducted, and their level of synergy was determined (Pagliosa, Tortorella and Ferreira, 2019). In another aspect, it was questioned how LM can be operated in DT environments. Research by Schumacher *et al.* (2022) identified 10 guidelines for a system where LM principles and Industry 4.0 technologies are synergistically integrated. Further, in a synergetic integration referred as 'Lean 4.0', Rossi *et al.* (2022) shown the characterisation of integrated tools, a framework and trends that are derived from a literature review and content analysis. In a more specific application focuses on Lean Automation where Lean Manufacturing principles are combined with a DT technology (Rossini *et al.*, 2022). The study to characterises the components of integration and shows that this specific integration leads to improvements in operational performance. In a broader aspect, a very recent study, Hines *et al.*, (2023) focused on various aspects of research and researchers that lead the research on integration of LM and Industry 4.0. The study identified the engineering-based background of researchers and increase in management aspects, the lack of clear terminology used in the field such as 'Lean 4.0', or 'Lean Industry 4.0.' and identified research gaps and future directions.

Title	**Summary**	**Findings**	**References**
Industry 4.0 and Lean Management -- Synergy or Contradiction?	The study examines the synergies of Industry 4.0 technologies towards a smart factory with LM principles through an interdependence matrix.	There are synergies between Industry 4.0 technologies and LM tools such as VSM, work standardisation	(Sanders *et al.*, 2017)

		supports prerequisites of Industry 4.0.	
Industry 4.0 and Lean Manufacturing: A systematic literature review and future research directions	This research uses systematic literature review to review the relationship between Industry 4.0 technologies and LM principles.	The study shows different level of synergies between the categories Industry 4.0 technologies and LM principles, where out of 126 relationships 24 of them ad high level of synergy.	(Pagliosa, Tortorella and Ferreira, 2019)
Lean Production Systems 4.0: systematic literature review and field study on the digital transformation of lean methods and tools	Using systematic literature review methodology, the digital transformation potential of LM principles is analysed.	Through analysing 62 papers, 10 guidelines is produced for a synergetic system that combined DT technologies with LM principles.	(Schumacher *et al.*, 2022)
Lean Tools in the Context of Industry 4.0: Literature Review, Implementation and Trends	This research uses systematic literature review, bibliometric and content analysis to identify evolution of LM principles	The findings characterise Lean 4.0 tools, propose a framework and show the main	(Rossi *et al.*, 2022)

	in the context of Industry 4.0.	trends in the industry.	
Lean Production and Industry 4.0 integration: how Lean Automation is emerging in manufacturing industry	Through distributing a survey to 200 manufacturing companies, the study investigates Lean Automation as an example of integration LM and Industry 4.0 technology.	The study identifies the components of Lean Automation and shows improvement in operational performance.	(Rossini *et al.*, 2022)
Lean Industry 4.0: Past, present, and future	A qualitative method based on open-question survey was distributed with the aim of previous, current, and future trends involving integration of LM and Industry 4.0 among academia.	The study explored the backgrounds and interests of researchers, popular terminologies, and identified research gaps.	(Hines *et al.*, 2023)

Table 2.7 Summary of literature that examine relationship of LM principles with DT technologies

2.4.1.2 Overview of Case Studies Integrating LM principles and DT technologies

To investigate the specific relationship of LM principles and DT technologies, during this PhD a systematic literature review was completed that examined case studies in manufacturing companies that had integrated application of LM tools and digital technologies part of Industry 4.0 (Yilmaz *et al.*, 2022). The overarching aim was to get insight of LM and DT integration in practical cases, showing which specific LM principles are integrated with which DT technologies. Taking the findings of this systematic literature review as a foundation, Table 2.8 was produced along with supporting literature through the course of the PhD. One of the important aspects of integrating LM and DT is regarding the application order of LM principles and DT technologies. The data showed that 90% of joint applications had LM principles applied first or simultaneously with DT technologies. One of the main reasons for applying LM first rises from the fact that waste elimination principle of LM would remove efficiencies in the processes. Otherwise adopting DT technologies in inefficient process would amplify inefficiencies (Bortolotti and Romano, 2012; Chiarini and Kumar, 2020). This is supported by the case studies on three SMEs that developed the with the aim of "Lean First … then Automate" (Powell, Morgan and Howe, 2021). In terms of applying LM principles simultaneously, literature review identified that DT technologies are used for two reasons, firstly LM principles are also used remove barriers of DT and to amplify the effect (Yilmaz *et al.*, 2022).

LM principle	Application order in respect to DT	Integration Item	References
Eliminate Waste	Simultaneous	[VSM] Value Stream Mapping is used together with digital technologies, mostly with simulation to visualize processes and tackle company specific problem.	(Al-Aomar, 2011; Gjeldum, Veža and Bilić, 2011; Tabanli and Ertay, 2013; Parthanadee and Buddhakulsomsiri, 2014; Schmidtke, Heiser and Hinrichsen, 2014; Helleno *et al.*, 2015; Prasath, Naveenchandran and Thamotharan, 2015; Yang *et al.*, 2015; Alvandi *et al.*, 2016; Andrade, Pereira and Del Conte, 2016; Guner Goren, 2017; Alzubi *et al.*, 2019; Huang *et al.*, 2019; Munyai *et al.*, 2019; Parv *et al.*, 2019; Baumer-Cardoso *et al.*, 2020; Jordan *et al.*, 2020; Lyu, Chen and Huang, 2020; Atieh, Cooke and Osiyevskyy, 2023)
	Before	[8 Types of Waste] Waste elimination including 8 types of waste need to be applied before adoption of DT. The aim is to not waste resources on digitizing waste.	(Bortolotti and Romano, 2012; Bittencourt, Alves and Leão, 2019; Powell, Morgan and Howe, 2021)

JIT/Flow	Before	[Kanban] Signal based production control is used prior and digital technologies such as simulation for JIT optimisation.	(Phumchusri and Panyavai, 2015; Che Ani, Kamaruddin and Azid, 2018; Azouz and Pierreval, 2019)
	Simultaneous	[JIT] Products are classified into groups with similar processing or routing requirements according to JIT for digital technologies such as robotics and automation.	(Boudella, Sahin and Dallery, 2018)
Continuous Improvement	During	[Kaizen] Kaizen and other CI tools are used to tackle DT implementation problems	(Peças *et al.*, 2021; Dinis-Carvalho *et al.*, 2023)
	Before and Simultaneous	[Visual Control] Visual management tools have been adopted to enable adoption of DT.	(Fenza, Loia and Nota, 2021; Dinis-Carvalho *et al.*, 2023; Eriksson *et al.*, 2023)
Standard Work	Before and Simultaneous	[Standardisation] Standardized work is used and enable adoption of DT.	(Bittencourt, Alves and Leão, 2020; Frédéric *et al.*, 2022; Medyński *et al.*, 2023)
Built-in Quality	Simultaneous	Problem solving techniques have been used with digital technologies to address problems.	(Camarillo, Ríos and Althoff, 2018; Vo *et al.*, 2020; Peças *et al.*, 2021; Barsalou, 2023)

	Before	Defects and quality issues are monitored prior to DT adoption.	(Guillen *et al.*, 2018; Ito *et al.*, 2020)
People & Teamwork	Before	[Respect for People] Employee suggestions/recommendations are considered for processes.	(Ballé *et al.*, 2014; Lorenz *et al.*, 2018; Saxby, Cano-Kourouklis and Viza, 2020)
	Before	[Involved Employees] Shop-floor employees took part in application of digital technologies.	(Oesterreich and Teuteberg, 2016; Tortorella *et al.*, 2021)

Table 2.8 Overview of literature focusing on LM principles as supporter of DT

2.4.2 Current Research and Gaps in Literature

There are various literature focusing on LM and DT technologies over the last as shown in Table 2.9. Firstly, a conceptual framework is missing where LM integrates with digital technologies, where this framework needs to be empirically analysed further to identify which digital technologies will complement which LM principles and their benefits (Kolberg *et al.*, 2017; Bittencourt, Alves and Leão, 2020). Although there is literature with existing framework, these are limited as they require validation in large sample and do not include human related aspects (Ciano *et al.*, 2021). Hence, a conceptual framework that links LM for adoption of DT that is quantitatively analysed on a large sample enough for statistical validation will add on a gap existing in literature. Taking a step further, recent research has suggested using secondary quantitative data and data triangulation to refine and understand of the links between LM and digital technologies (Dixit, Jakhar and Kumar, 2022).

There is a gap in literature validating the positive impact of LM principles for DT technologies adoption in a larger sample. While the benefits of LM on adoption of digital can be identified systematically, the current research lacks depth (Bittencourt, Alves and Leão, 2020). Two recent research using case study methodology also revealed applying LM has facilitating role on application of DT, however both listed their main limitation as small sample size and outlined the need for validation on a large sample (Ciano *et al.*, 2021; Rossini, Powell and Kundu, 2022). Further, as future research suggestion Ciano *et al.* (2021) specifically proposed surveys and once the validation has been achieved the next suggestion was to build a link between specific LM tools and DT technologies.

Further, the benefits of DT technology adoption through LM require empirical evidence as identified by recent studies (Pagliosa, Tortorella and Ferreira, 2019; Buer, Strandhagen, *et al.*, 2020). Conducting a survey with 76 respondents, Buer, Semini, *et al.* (2020) concluded that when used together LM and digital technologies can lead to improvements in operational performance. However, one of the main limitations was the sample size and future research suggestion is directed at investigation and statistical analysis of specific links between LM and DT adoption with its relation to operational performance.

Reference	**Findings**	**Limitations and Future Research Directions**
(Bittencourt, Alves and Leão, 2019)	It simplifies processes and eliminates waste in a way that it is not repeated, reduces the possibility of compromising scarce resources, and increases the transparency. of work processes/organization.	The depths of LM and DT need to be discovered further.
(Pagliosa, Tortorella and Ferreira, 2019)	The synergetic relationship between specific LM and digital technologies have been identified.	Empirical evidence on a large sample is needed to validate the findings on provide the synergistic relationship where survey is suggested. Another future direction is examination of these relationship to operational performance.
(Rossini *et al.*, 2019)	Through survey of 108 respondents, the study investigated the relationship between the adoption of LM	The limitation was due to the small sample size. Future survey-based studies with larger sample size that allows complex statistical analysis is suggested.

	principles and Industry 4.0 technologies. The finding was that the earlier adoption of LM principles results in adoption in Industry 4.0.	A further gap in literature identified on building specific relationships between LM and DT.
(Bittencourt, Alves and Leão, 2020)	A systematic literature review analysed 33 papers to show Lean acts as an enabler for Industry 4.0 technologies	The limitation was related to people centric approaches for Lean as an enabler. Further, people aspect needs to be better integrated to framework and empirical evidence is needed.
(Ciano *et al.*, 2021)	Using multiple case study methodology, a framework is constructed between LM practices and Industry 4.0 technologies.	The main limitation is the sample size due as the research adopted case study methodology. As future direction, empirical evidence is needed on larger sample for validation. Survey was suggested.
(Rossini *et al.*, 2021)	Companies that have strong LM maturity shape and implement DT differently compared to the ones with lower LM maturity, suggesting high LM maturity enables DT adoption.	Small sample size with 19 case studies was identified as a limitation. Future research direction was based on validation of facilitating role of LM on a larger sample size.
(Dixit, Jakhar and Kumar, 2022)	The study showed that lean and sustainable manufacturing lead to adoption of Industry 4.0. Only three aspects of LM were considered in the study that are	The sample size was from one point from each manufacturing organisation, limiting the study. Future empirical evidence and secondary data is required to test the relationships of LM and DT. The study

	JIT, Quality and Employee Engagement.	also included only limited principles included in LM.

Table 2.9 Overview of the literature focusing on research gap

In summary, research gaps can be summarized as follows: firstly, there is a need for larger sample sizes to validate the impact of LM principles in DT technologies. Secondly the development and quantitative analysis of a conceptual framework is required, one that thoroughly examines the compatibility of LM principles to DT technologies. Lastly, there is a need for empirical evidence to substantiate the operational benefits of adopting DT through LM in a country-specific context, with an emphasis on studies employing larger sample sizes for more robust statistical analysis, as existing research in this area is constrained by limited sample sizes.

2.5 Chapter Summary

In this chapter, the literature related to LM principles, DT technologies, and operational performance within the context of manufacturing SMEs, particularly in Turkey, has been reviewed. Addressing identified research gaps, the contribution of this study lies in developing a conceptual framework accompanied by quantitative analysis to explore the correlation between LM principles, DT transformation, and their impact on operational performance. This chapter has consolidated existing research gaps, establishing a foundation for the proposed conceptual model. In the next chapter, the theoretical underpinnings and the development of hypotheses related to the conceptual model are discussed in detail.

Chapter 3: Conceptual Model and Hypothesis Development

3.1. Chapter Introduction

The previous chapter provide an extensive review relevant to this study, highlighting the necessity for a comprehensive conceptual framework to investigate the connections between LM principles, DT technologies, and operational performance with literature (Ciano *et al.*, 2021; Rossini, Powell and Kundu, 2022). This chapter advances the discussion by providing a detailed explanation of the theoretical underpinnings of the subject, along with an outline of the theoretical contributions of this study. It then proceeds to introduce the proposed conceptual framework and the hypotheses that have been developed as a result.

3.2. Theoretical Context

A theory is often serving as the foundation for practice while challenging and expanding existing knowledge designed to explain, predict, and understand phenomena (Foroudi and Dennis, 2023). Although theory do not bring out a comprehensive depiction of the entire scenario, they serve as pointers to crucial factors showing significant parts of a larger narrative of causation (Powner, 2015). Hence, to achieve the aims of the research, it is important to theory developed previously concerning LM and DT that depict the comprehensive understanding and build on to the theory. In the research that combines LM and DT, the theoretical approach has centred on institutional theory and contingency theory, as indicated in Table 3.1.

Theory	**Research Context**	**Theoretical Stance & Findings**	**Reference**
Institutional Theory	LM and digital technologies were assessed in a framework aligned with institutional theory.	Several LM tools were combined with digital technologies that considered environmental dimensions as part of institutional theory and isomorphism.	(Qureshi *et al.*, 2023)
Institutional Theory	LM and ERP systems were integrated	Through carrying out experimental study with 144 participants in Egypt,	(Abobakr, Abdel-Kader and Elbayoumi, 2022)

	through institutional theory	integration of LM and sustainable ERP was examined considering isomorphic forces	
Contingency Theory	The research focused on Industry 4.0's implementation to moderate LM adoption for performance.	Based on contingency theory, the study examined of theory-based contingencies for adoption of LM and Industry 4.0. The findings revealed that contingencies have limited effect on the financial performance.	(Tortorella, Giglio and van Dun, 2019)
Contingency Theory	The aim was to critical success factors of Industry 4.0 that included LM principles like Continuous Improvement	Contingencies such as firm size, competitiveness and organisational culture were taken into consideration while assessing the critical success factors.	(Pozzi, Rossi and Secchi, 2023)
Institutional Theory, Contingency Theory	Neo-institutional theory was employed to depict lean, agile manufacturing companies to incorporate digital technologies into their operations	Using the neo-institutional theory, service-oriented manufacturing companies are defined and the extend of digital technology adoption is investigated in relation to contingencies such as company size and sector.	(Vilkas *et al.*, 2022)

Table 3.1 Overview of theoretical stance of recent literature combining LM and DT

This is consistent with the research on LM and DT separately. For LM, institutional theory and contingency theories have been identified as one of the core theories that have been closely investigated through organisational behaviour (OB) (Danese, Manfè and Romano, 2018; Aripin *et al.*, 2023). More specifically, OB theories allow understanding how the individuals part of the organisations behave where successful implementation of LM on aligning the operational strategy with OB theories (Punnakitikashem *et al.*, 2009). Similarly, a literature review revealed that contingency and institutional theories are among the most utilised theoretical lenses utilised to research digital technologies part of Industry 4.0 (Demartini and Taticchi, 2022). This is similar with the research combining LM and DT as seen in Table 3.1. which will be explained further with detailed explanation of each theory.

Institutional theory focuses on the idea that institutions or a company in this context grow very similar to each other due to underlying forces (Powell and DiMaggio, 1991). It is related to isomorphism, where a company resembles the other one when encountered with similar environmental circumstances. Isomorphism is divided in three mechanisms that are coercive, mimetic, and normative (DiMaggio and Powell, 1983) where the organisations where organizations adopt similar practices due to pressures from external authorities such as regulators, imitation of successful models, and conformity to prevailing norms, respectively. These forces can be explained using the study of Abobakr, Abdel-Kader and Elbayoumi (2022) which highlighted the institutional theory and underlying isomorphic mechanisms that drive the concurrent adoption of LM and sustainable ERP systems in Egyptian manufacturing companies. The coercive force came in to play where the companies encouraged to follow Egyptian government's legislation on ERP system implementation, mimetic pressure was checking and adopting successful company's ERP solutions and normative was conforming to International Standardization Organization (ISO) for adoption of LM and ERP practices. Similarly, recent research focusing on sustainable supply chains aligned the research with institutional theory when adopting LM principles and digital technologies as environmental factors are considered in accordance with isomorphism (Qureshi *et al.*, 2023).

While institutional theory serves as a valuable lens for understanding organizational behaviour, it has limitations. A key limitation of institutional theory is its assumption of uniform outcomes, overlooking the contextual variability of organizations that is shaped by interacting actors who establish shared rules and practices (Kelling *et al.*, 2021). It has been argued that the theory often overemphasizes isomorphic pressures that drive uniformity, creating a picture of homogenous outcomes among organizations, while neglecting the different possible ways organizations adapt to their institutional environments, making it inadequate for fully explaining organizational responses (Geels, 2020). Further supporting this critique, Akenroye *et al.* (2024) highlights that institutional theory fails to account for the unique operational and cultural characteristics of SMEs, which play a crucial role in shaping their outcomes. By treating organizations as uniformly influenced by institutional pressures, institutional theory disregards the distinct attributes and challenges faced by SMEs in different contexts. To address this gap of uniformity, the study will examine research gaps, particularly the absence of contextual variability and SME-specific traits such as company size and sector, to shape the conceptual framework.

One approach is to expand the theory by integrating it with complementary frameworks is to expand theory by integrating it with complementary frameworks (Aripin *et al.*, 2023), such as contingency theory, to account for variables like company size, offering a solution tailored to SMEs and accommodating their unique characteristics (Netland, 2016). This integration aims to provide a better understanding of organizational behaviour across diverse contexts and has been explored by previous literature (Ketokivi and Schroeder, 2004; Vilkas *et al.*, 2022), where LM principles is approached from a technological perspective that incorporates organizational size and complexity. However, both models lacked a comprehensive integration of variety of LM and DT technologies, focusing instead on a single LM and DT technology.

Contingency theory points out that organizations align their practices with their internal and external environment (Netland, 2016). According to this theory, an organization's operational performance, including the adoption of DT technology, relies on the alignment of contextual factors (Yusuf *et al.*, 2023). In alignment, many studies including Pozzi (2023) included contextual factors such as company size and structure to assess the adoption of DT technologies. The factors that are concerned with adaptation are described as contingencies and classified to include company size and structure that the company adopt (Otley, 1980). Further, research over years has focused on company size over the years as an important factor to assess operational performance as it has effects on resource availability and flexibility that affect operational performance (Netland, 2016; Fenner and Netland, 2023). Table 3.2 below outlines key contingency factors, such as company size, sector, and location, which are important for operations and strategies in the manufacturing sector.

Contingency Factor	References
Company Size	(Van Looy and Van den Bergh, 2018; Ongena and Ravesteyn, 2020; Couckuyt and Van Looy, 2021; Shala, Prebreza and Ramosaj, 2021; Bhatia and Kumar, 2022; Pozzi, Rossi and Secchi, 2023; Yusuf *et al.*, 2023; Ahmad, Van Looy and Shafagatova, 2024)
Company Sector	(Van Looy and Van den Bergh, 2018; Ongena and Ravesteyn, 2020; Couckuyt and Van Looy, 2021; Bhatia and Kumar, 2023; Ahmad, Van Looy and Shafagatova, 2024)
Location	(Van Looy and Van den Bergh, 2018; Couckuyt and Van Looy, 2021; Bhatia and Kumar, 2023; Ahmad, Van Looy and Shafagatova, 2024)

Table 3.2 Overview of important contingency factors

While contingency theory provides valuable insights into the alignment of practices and contextual factors (Parast, 2022), it has certain limitations. Research indicates that contingency theory fails to offer a comprehensive framework for explaining organizational outcomes and is challenging to apply due to the numerous contextual factors that must be considered and interconnected (McAdam, Miller and McSorley, 2019; Shenkar and Ellis, 2022). Hence, contingency theory has been to be supplemented with additional frameworks over time (Aripin *et al.*, 2023). Research integrating DT and LM show that contingency variables by themselves have little impact to explain outcomes of performance, where the available frameworks lack a sufficiently integrated perspective to capture the combined effects of external pressures and variety of contextual factors (Ketokivi and Schroeder, 2004; Tortorella, Giglio and van Dun, 2019; Shala, Prebreza and Ramosaj, 2021). For example, a study applying contingency theory to Lean Automation acknowledged the need to place greater emphasis on measuring operational performance, noting that the concurrent use of LM principles and DT technology does not inherently lead to improved performance (Tortorella, Narayanamurthy and Thurer, 2021).

This underscores the gap in existing contingency theory literature, where operational performance considerations should be more explicitly integrated.

This research proposes to expand theory by incorporating institutional theory with contingency theory. By combining both, the framework enables a more comprehensive analysis that considers contextual variables, and this refinement accounts for organizational diversity. This integration is mutually beneficial: institutional theory's tendency for overgeneralization and neglect of contextual factors (Geels, 2020; Kelling *et al.*, 2021; Fogaça, Grijalvo and Neto, 2022) is addressed by contingency theory's focus on contextual variables, while contingency theory's limitations in uniformity and practical application (McAdam, Miller and McSorley, 2019; Parast, 2022; Shenkar and Ellis, 2022) are mitigated by the institutional theory that assumes organisations behave similarly. Next section will build upon and elaborate on how theoretical framework is derived based on institutional theory and supported by contingency theory. It will introduce and refine a conceptual model that visualize the relationships and dynamics between LM principles, DT technologies, and operational performance, providing a more structured framework for understanding these complex interactions.

3.3. Conceptual Framework

To effectively understand and explore the conceptual frameworks, it is essential to explain the institutional theory which emphasizes how cultural, cognitive, and economic factors influence organizational behaviour, with a focus on achieving social approval alongside efficiency (Sahin and Mert, 2023). Deriving from institutionalism, neo-institutionalism has also an economic focus where organisations imitate each other in the pursuit of better economic outcomes (Haunschild, 1993; Ketokivi and Schroeder, 2004). This perspective is particularly relevant to our current research, which concentrates on operational performance. Through neo-institutionalism, Ketokivi and Schroeder (2004) set out a framework is to shows the adoption of innovative practices as displayed in Figure 3.1. This framework has three stages using strategic goals, institutional effects and environmental contingencies showing that it is inclusive of the contingency theory.

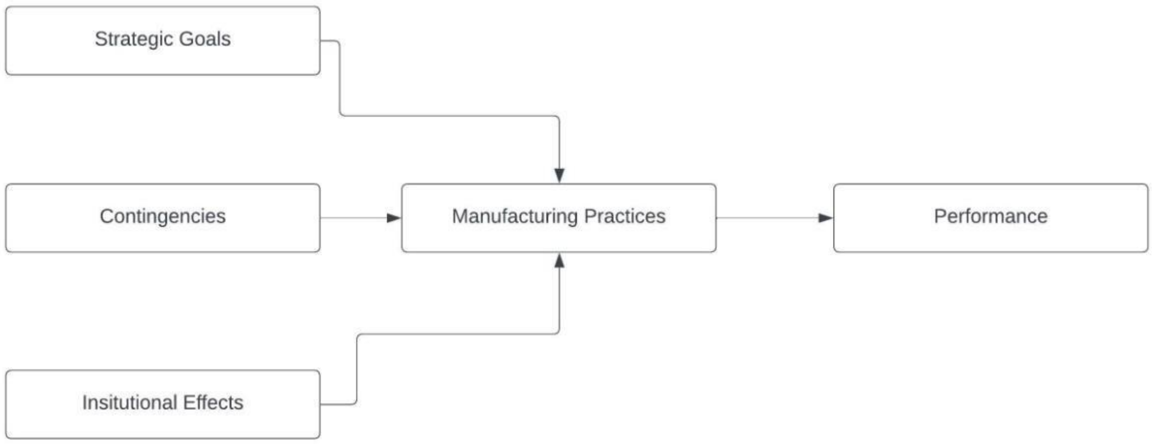


Figure 3.1 Theoretical Model developed by Kekokivi and Schroeder (2004)

This study will be grounded in institutionalism theory and research utilises framework used by Ketokivi and Schroeder (2004). As the research objective focuses on increasing the operational performance, this aligns perfectly with neo-institutionalism and its economic focus. In recent studies, this framework is used for digital transformation practices where Bokrantz *et al.* (2020) utilized the framework for application of Smart Maintenance as part of Industry 4.0. In the centre of the framework was smart maintenance as modernised operations, which led to plant performance and consequently firms' performance. Similarly, in another recent research by Vilkas *et al.* (2022) used the framework where adoption of digital technologies was at the center. The proposed framework for this study is displayed in Figure 3.2, the DT technologies is at the centre so institutional theory can provide insight on the external factors that lead to adoption of DT as part of manufacturing practices.

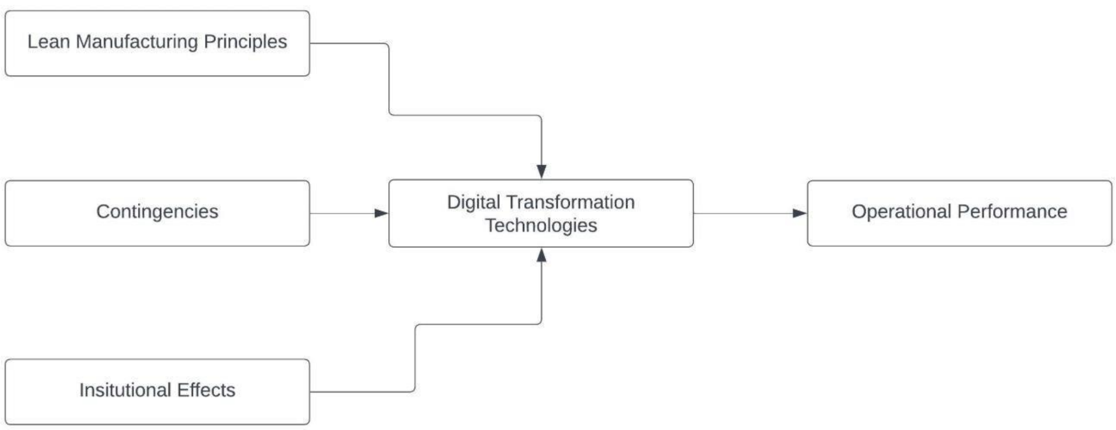


Figure 3.2 Theoretical Framework for this study

Lean Manufacturing (LM) can be defined as a strategic objective, emphasizing the adoption of LM principles. This perspective is supported by Vilkas et al. (2022), who identified being 'Lean' as a strategic goal alongside agile and service-oriented manufacturing, with the primary focus on exploring the integration of digital technologies. Within the same framework of that study, contingencies are chosen as company size, sector, and location. Likewise, this study employs these identical variables as also selected in supporting studies as part of SME conditions introduced in Chapter 2. These contingencies act as control variables, helping refine the framework by moving beyond broad assumptions to focus on specific characteristics. For instance, Akenroye *et al.* (2024) highlighted that SMEs have unique traits often overlooked by institutional theory. By incorporating these variables, companies with similar traits can be grouped, addressing limitations, and enabling more detailed analysis of specific groups, such as SMEs. Contingencies, initially part of the framework, have been omitted as they primarily function as control variables rather than a construct as seen in Figure 3.2.

In this section, the conceptual framework for our study is proposed which is based on the model developed by Ketokivi and Schroeder (2004) and further strengthened by recent research (Bokrantz *et al.*, 2020; Vilkas *et al.*, 2022). The proposed framework consists of four principal constructs: Lean Management (LM) principles, Institutional Effects (IE), Digital Transformation (DT) technologies, and Operational Performance (OP). Overall, this theoretical framework allows incorporation of both contingencies and institutional pressures as identified as core theories involving integrated research on LM and DT. Contingency variables were defined as company size, sector, and manufacturing complexity as noted by literature and Table 3.2 (Bhatia and Kumar, 2022). Combining this theoretical context introduced in this section with research problem and objectives introduced in previous sections, the conceptual framework is further elaborated in the following section.

3.3.1. Institutional Effects and DT technologies

Institutional theory stems from the idea that institutions are similar due to the external pressures (DiMaggio and Powell, 1983). There are three different pressures, which are called mimetic, coercive and normative, that cause institutions to create, shape and form their existing standards, structures, and forms (Aripin *et al.*, 2023). This section explains each type of institutional pressure, referencing Table 3.3 for definitions and their sources, while Tables 3.4 provide details on the measurement scales.

	Item	Pressure Source
Mimetic Pressures	Organizations imitate others in their industry, leading to similarities in products and practices.	Competitors
Coercive Pressures	Organizations follow external rules or standards, creating uniformity in products and processes.	Government, Regulatory agencies, Industry Associations, Customer Requirements
Normative Pressures	Professionals in an industry develop shared ways of thinking, causing uniformity	Industry Professionals

Table 3.3 Overview of Institutional Effects (St. John, Cannon and Pouder, 2001; Gupta et al.*, 2022; Kauppi, 2022)*

Mimetic pressures are the tendency of organizations to replicate the actions of successful competitors or peers arises when companies within an industry due to gain benefits, leading to similarities in products and practices (St. John, Cannon and Pouder, 2001; Kauppi and Luzzini, 2022). To stay competitive, it is crucial for businesses to react to the actions and conduct of their rivals (Latif *et al.*, 2020). A key example is Toyota's production system, which inspired many companies to copy its methods, leading to the rise of Lean Manufacturing (Holweg, 2007). In manufacturing, adopting LM principles are often viewed as imitation driven by the benefits it offers (St. John, Cannon, and Pouder, 2001). From another perspective, companies often imitate each other to enhance their perceived value and reputation in line with industry. For example, implementing DT technologies like ERP conveys an image of streamlined operations, improved processes, and effective target identification, which can significantly boost a company's valuation during mergers and acquisitions (Deloitte, 2018). Hence, perception of value and reputation along with the gained benefits are important measurement scales for mimetic pressures as included in Table 3.4.

	Measurement Item
Mimetic Pressures	Our main competitors who have adopted DT technologies have greatly benefitted
	Our main competitors who have adopted Industry 4.0 are favourably perceived by others within the same industry and customers
Coercive Pressures	The government requires us to adopt DT technologies
	Our customers require us to adopt DT technologies.
Normative Pressures	Our customers have adopted DT technologies.

	Our suppliers have adopted DT technologies.

Table 3.4 Measurement Scale for Institutional Effects adapted from Gupta et al. (2020)

Coercive pressure arises from regulations and policies imposed by governments, industry standards, or other industry shareholders and stems from demands on which the targeted organization depends, often enforced in a manner that compels compliance (Sony and Aithal, 2020). In addition, customer requirement is also viewed as coercive pressure by many notable literatures as an organisation need to comply a standard or a demand set by its customers (Moyano-Fuentes, Sacristán-Díaz and Martínez-Jurado, 2012; Gupta *et al.*, 2022; Kauppi, 2022). For instance, the largest food retailer in the Netherlands, Albert Heijn, mandates that its private-label cocoa products hold Fair Trade certification according to its social compliance strategy (Albert Heijn, 2021). This places coercive pressure on cocoa manufacturers, as suppliers, to comply with these standards to sell their products. This requirement comes not from government regulation as there is no specific requirement but from the demands of large retailers acting as customers (CBI, 2024). Hence, coercive pressure is included as both pressure from government and customer requirement.

Normative pressures, shaped by experienced stakeholders in the field, play a significant role in influencing norms, particularly in developing countries, with customers and suppliers being key sources of such pressures (Latif *et al.*, 2020; Gupta *et al.*, 2022). In terms of customers the increasing adoption of digital technologies has reshaped market dynamics, aligning customer expectations with industry norms, where these expectations themselves become an integral part of the standard (Riedl *et al.*, 2024). The adoption of DT technologies, by both customers and suppliers can establish an industry standard, compelling companies to implement similar practices. For example, when multiple suppliers collaborate in the design, production, and supply of components, particularly in industries like automotive, the use of Computer-Aided Design (CAD) software and simulation tools often becomes a standard practice, creating an industry norm (Vido, de Oliveira Neto, *et al.*, 2024).

3.3.2. Final Conceptual Framework

The comprehensive version of this conceptual model is illustrated in Figure 3.3. This framework integrates Institutional Effects, LM principles, DT technologies, and operational performance metrics as previously discussed in Sections 2.3 and 2.4. The proposed conceptual model conveys the relationships between these constructs, with hypotheses mapped to examine the influences of each component. Grounded in institutional theory, H1 hypothesizes that Institutional Effects influence the adoption of DT technologies. As a central focus of this research, H2 posits that LM principles affect the adoption of DT technologies and H3 hypothesizes that DT technologies impact operational performance.

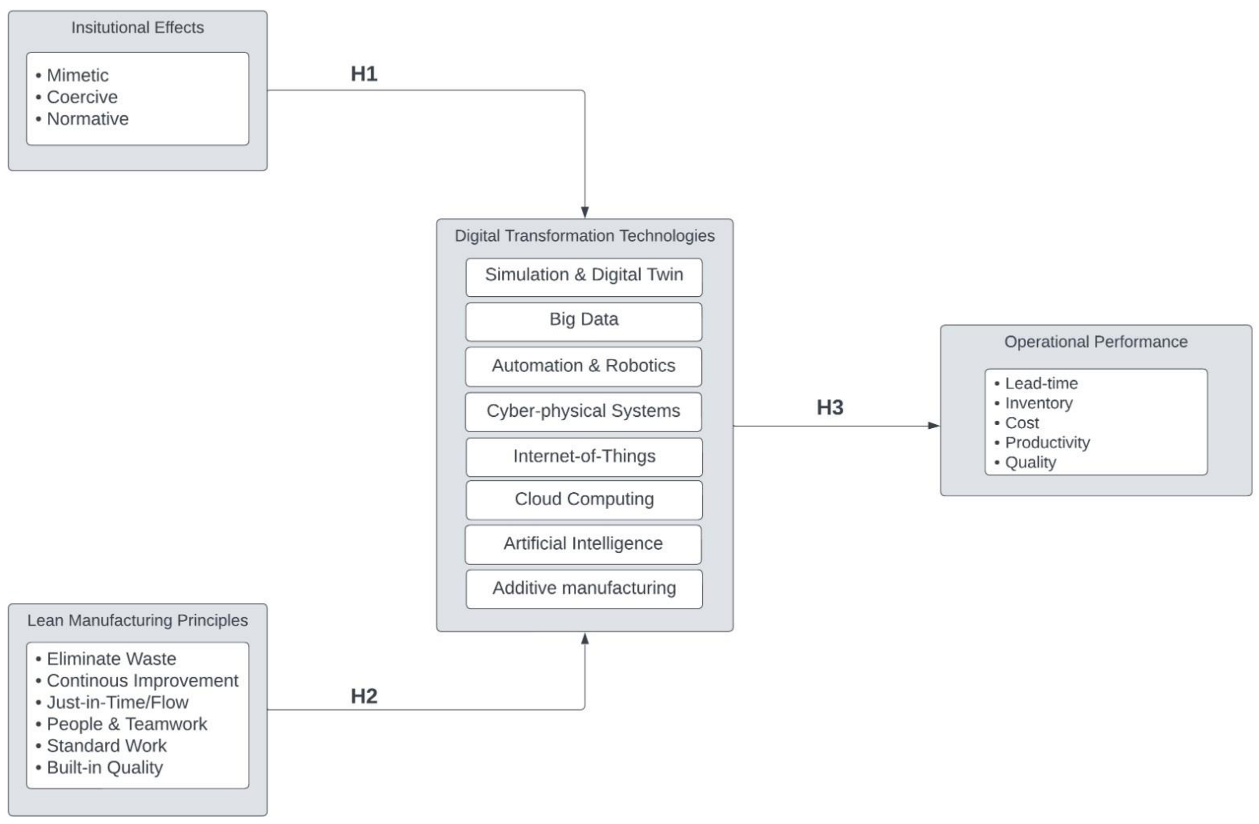


Figure 3.3 Detailed Conceptual Framework

The conceptual framework proposed in this study provides the necessary theoretical underpinnings, as well as a thorough structure that captures the complexities of the research subject. As noted in Section 2, existing research has not succeeded in presenting a comprehensive framework that encompasses the three primary constructs and their sub-elements (Kolberg *et al.*, 2017; Ciano *et al.*, 2021). This research offers a cohesive model that encapsulates the interplay between LM principles, DT technologies, and operational performance.

Code	Hypothesis
H1	Institutional Effects have a positive effect on adoption of Digital Transformation technologies Lean
H2	Manufacturing Principles have a positive effect on adoption Digital Transformation technologies
H3	Digital Transformation Technologies have a positive effect on Operational Performance

Table 3.5 Overview of the Hypotheses

The overview of Hypothesis derived from the conceptual framework of Figure 3.3. are presented in 3.5. H1 suggests that institutional effects can aid DT adoption in SMEs, where, for example, coercive pressures from policymakers, such as regulations or compliance requirements, play a role in encouraging DT technology adoption. H2 considers how Lean Manufacturing principles, including waste elimination and process standardisation, aid the DT adoption process. H3 proposes that the adoption of DT technologies, including applications such as additive manufacturing, is linked to improvements in operational performance, with potential outcomes in areas such as lead time and quality. Together, these hypotheses form an integrated perspective on how external pressures, LM principles and DT technologies interact to shape performance outcomes in SMEs.

This framework, together with the proposed hypotheses, offers a novel contribution to LM-DT research, through offering a comprehensive integration of LM principles, DT technologies, and operational performance within a single theoretical model grounded in institutional theory and complemented by contingency theory. While previous models, such as Ketokivi and Schroeder (2004) and Vilkas *et al.* (2022), have incorporated elements they typically focused on a single LM or DT technology and did not fully capture the breadth of possible technologies or their combined impact on performance. Moreover, prior frameworks have often overlooked SME-specific contingencies such as company size, sector, and manufacturing complexity, treating organizations as uniformly affected by institutional pressures (Kelling *et al.*, 2021; Abobakr, Abdel-Kader and Elbayoumi, 2022; Qureshi *et al.*, 2023). By including these contingencies as control variables and examining their interaction with institutional effects, this study expands the theoretical model of earlier work and provides a detailed framework for analysing performance outcomes in diverse manufacturing environments.

3.4. Chapter Summary

In this chapter, the theoretical underpinnings are first explained, highlighting the significance of institutional and contingency theories. Each theory is explored in depth, addressing its importance and limitations. To overcome these limitations, a combination of both theories is proposed, leveraging their strengths to complement each other (Aripin *et al.*, 2023). Building on this, a framework predominantly focused on institutional theory, which also incorporates aspects of contingency theory, is introduced as the foundation for the proposed framework (Ketokivi and Schroeder, 2004). This framework is further elaborated through an extensive literature review, detailing its constructs, which include LM principles, DT technologies, institutional effects, and operational performance. Accompanying this framework, three main hypotheses have been developed to further investigate the interrelationships among these constructs.

Chapter 4: Research Methodology

4.1. Chapter Introduction

In preceding chapters, the research questions, the conceptual framework, and the associated hypotheses were established. To effectively address and achieve the research objectives, it is important to identify an appropriate research methodology. This chapter provides a comprehensive examination on the research methodology as a systematic and structured plan to address the research questions. Philosophical considerations along with research ontology, epistemology and approach need to be explained establishing the foundational beliefs and strategies behind this study (Saunders, Lewis and Thornhill, 2012; Hair Jr., Page and Brunsveld, 2019). In the next section, research choices are explored with introducing the chosen research method along and justifying why this method is well-suited for this study. Afterwards, next section provides detail on research design outlining step by step details, from of questionnaire design, content, and form of choice. The data analysis and statistical techniques employed to test hypothesis are explained to show how they research questions are addressed. The chapter is concluded by summarising the research methodology and the structured approach to make sure that the research objectives are met.

4.2. Research Philosophy

Research philosophy reflects a researcher's the understanding of knowledge and assumptions made to perceive the world (Saunders, Lewis and Thornhill, 2012), guiding the research approach, strategy and the interpretation of results. To define the research philosophy, researchers adopt ontological and epistemological positions where ontology focusing on the nature of reality, what exists, and what is worth studying, while epistemology explores the possibilities, limits, and methods of understanding and acquiring knowledge (Hansen, 2006). The following section explains the research ontology and epistemology for this study and provides justification for the selected choices. Afterwards, research approach will be explained where the philosophical considerations build the foundation for the methodological choices and how they answer the research questions.

4.2.1. Research Ontology

Research ontology revolves around researchers' beliefs about the nature and the essence of social reality, including assertions about its existence, appearance, constituent components, and the interactions between these elements (Grix, 2002; Blaikie, 2010). According to Burrell and Morgan (2017), business research is predominantly guided by two ontological perspectives that are realism and nominalism. Realism is an ontological stance takes accounts for to the observable events and occurrences we experience through our senses and accurately represent genuine aspects of the world where the 'reality' pertains to anything existing within the universe (Schwandt, 1997). Realism suggests that there is an unseen dimension of social reality that cannot be directly observed as social beings and encompassing underlying structures and mechanisms have observable social interactions and outcomes (Matthews and Ross, 2010). Nominalism, also called anti-realism, refer to viewpoints that challenge the existence of objective truths and the concept of a reality independent of human perception (Garrett and Cutting, 2015).

Realism ontology is suitable for the research as it emphasizes structures and mechanisms influencing have their effects observable through behaviour (Foroudi and Dennis, 2023), aligning with the study's goal to measure the impact of DT technology and operational performance in evaluating LM principles. One of the core principles of realism is the ability to study mechanisms through their observable outcomes (Matthews and Ross, 2010). For instance, the impact of operational performance of SMEs is measured by reflecting an ontological perspective that assumes reality can be observed and quantified. This approach is particularly relevant to addressing the identified literature gap, which highlights the need for empirical research and statistical analysis (Pagliosa, Tortorella and Ferreira, 2019; Rossini *et al.*, 2021). On the other hand, nominalism, which focuses on subjective and socially constructed realities (Garrett and Cutting, 2015; Burrell and Morgan, 2017), is less suitable for this study's objective of empirical measurement. Therefore, realism is chosen as the appropriate ontological approach for this research.

4.2.2. Research Epistemology

Following the research ontology, epistemology represents a crucial the aspect of philosophical considerations of the research. Epistemology, also known as the theory of knowledge, concentrates on what constitutes valid knowledge within a particular field of study (Audi, 2010; Saunders, Lewis and Thornhill, 2012). This field is primarily defined by two main epistemological stances that are positivism and interpretivism outlined in Table 4.1. Positivism argues that that reality is external and objective to the researcher and aims to reveal theories via empirical research, where knowledge can be observed and measured (Collis and Hussey, 2014). Interpretivism is contrast of positivism that the world is too complex to be approached in a structured way where the reality is subjective (Saunders, Lewis and Thornhill, 2012). Moreover, in interpretivism, the researcher engages directly with the subject of the research, whereas in positivism, the researcher maintains a detached and objective stance (Collis and Hussey, 2014).

Philosophical Assumption	Positivism	Interpretivism
Ontological Assumption	Social reality is objective and external to researcher	Social reality is subjective and socially constructed.
Epistemological Assumption	Knowledge comes from objective evidence about observable and measurable phenomena	Knowledge comes from subjective experience from participants.
	The researcher is distant from the study.	The researcher interacts with the study

Table 4.1 Comparison of Positivism and Interpretivism from Collis and Hussey (2014)

This research adopts positivism epistemological stance. Firstly, positivism aligns with the realism, involving the researcher on knowledge from the real world, analysing, and interpreting observable and quantifiable data through statistics and modelling within a structured research designs to achieve specific objectives (Rajagopal, 2017). In this study, the intended conceptual framework and related hypotheses are planned to be empirically validated through statistical analysis using the data gathered to fulfil the research objectives. Secondly, by focusing on the relationship between LM principles, DT technologies and operational performance, the researcher is not involved in the studies that aligns with positivism. Considering that the research relies on data empirical evidence and structured study and researcher is distant from the study, positivism is the epistemological stance that is optimally suited for this study as it aligns closely with the aims of this research.

4.3. Research Approach

After establishing research ontology as positivism, next is to analyse the research approach determined for this study. There are two different research approaches that are deductive and inductive are explained, as outlined in Table 4.2 below. Induction involves a priori arguments where empirical evidence is sought to test hypotheses, whereas deduction pertains to a posteriori argument where empirical investigation guides the formation of knowledge (O'Gorman and MacIntosh, 2014). While both approaches have their advantages and drawbacks, one is more suitable for achieving the objectives of a particular study. For this research, the deductive approach has been chosen as the more appropriate method.

	Deduction	Induction
Logic	In a deductive inference, when the premises are true, the conclusion must also be true.	In an inductive inference, known premises are used to generate untested conclusions.
Use of Data	To evaluate propositions	To explore a phenomenon, identify themes, create a conceptual framework
Theory	Theory falsification and verification	Theory generation and building

Table 4.2 Overview of research approaches from Saunders, Lewis and Thornhill (2012)

This research began with a detailed literature review, which provided a foundation for developing a conceptual framework. From this framework, hypotheses were constructed to guide the empirical testing process. The deductive approach was selected for this study because it emphasizes testing theories and propositions through verification or falsification (Saunders, Lewis and Thornhill, 2012). By structuring the study around predefined hypotheses, the deductive method allows for a systematic investigation of these relationships. In contrast, an inductive approach explores topics to identify emerging patterns or outcomes (Collis and Hussey, 2014), making it less aligned with this study's emphasis on hypothesis testing and structured analysis. Consequently, the research methodology chosen for this study is deductive, as it involves empirically testing the proposed conceptual framework that illustrates the interactions between LM principles, DT technologies, and operations, which is consistent with the principles of deduction.

4.4. Research Choice and Strategy

After establishing the philosophical considerations for the research, it is important to explain the research strategy which can be defined as a structured plan that the research questions are aimed to be addressed (Collis and Hussey, 2014). Adding forward from the philosophical considerations, quantitative research predominantly relates to positivism and deductive approach where the aim of using data is to test a theory (Saunders, Lewis and Thornhill, 2012). Quantitative research involves collecting numerical data that can be measured and analysed statistically, whereas qualitative research gathers non-numerical data, such as text or images, for analysis (Hair Jr., Page and Brunsveld, 2019). In line with research philosophy, to effectively address the research question, this study employs a quantitative research approach. The rationale for selecting this method is the need to address the research objectives, particularly the need to empirically validate conceptual model and the associated hypotheses. Additional support for this approach is drawn from identified gaps in the literature, which point to the necessity of conducting statistical analysis across a large sample size, as detailed in Section 2.4.2. The quantitative research methodology is essential for robust testing hypothesis and validating the conceptual model proposed in the study.

After deciding on positivist and deductive approach and quantitative research methodology, its crucial to select an appropriate research method. The relevant quantitative methods are identified as experimental studies and surveys as shown in the Table 4.3 below. Experimental studies are in true form doing experiments to prove or disapprove statements in a causal way (Saunders, Lewis and Thornhill, 2012). This methodology mostly used in natural sciences in controlled conditions such as chemistry labs (Collis and Hussey, 2014). This method is not relevant for this study as firstly, it is hard to do controlled research in manufacturing companies with complex and ongoing operations. Secondly, the number of experiments is limited, where a large sample is required to validate the framework. As noted, one of the gaps of literature is the low sample size of previous research (Kolberg *et al.*, 2017; Rossini *et al.*, 2021).

Research Method	**Description of the Method**	**Features**
Experimental Studies	Doing an experiment to test causal relationship, to prove or disprove a statement. Mostly used in natural sciences.	• Controlled environment is hard to achieve in business research • Establishes causality and replicable results • Small sample size
Survey	Survey involves asking set of question through a sample population. It aims to provide descriptive information on trends, attitudes of selected population.	• Useful to describe trends, patterns • It can include many variables • Large sample size

Table 4.3 Quantitative research methods (Saunders, Lewis and Thornhill, 2012; Collis and Hussey, 2014; Hair Jr., Page and Brunsveld, 2019)

Through collection of large quantitative data of a sample population, surveys enable description of trends and patterns (Czaja and Blair, 2005). Surveys commonly use questionnaires to create a standardized data to be distributed, collected, and analysed easily (Saunders, Lewis and Thornhill, 2012). The conceptual model constructed from theoretical knowledge is shown in Chapter 3 can be assessed using the survey questionnaire strategy. This allows to test on a large sample to detect trends and patterns of selected manufacturing SMEs. Further, the conceptual model in this study utilises large number of variables for LM principles and DT technologies. This fits with survey strategy as it allows inclusion of many variables, facilitating the exploration of connections and relationships between them (Morgan, 2014).

The rationale of choosing quantitative approach and surveys is further supported by the literature that adopted methodology as shown in the Table 4.4 below. It shows the quantitative data collection methodology along with method of data analysis. In research by Dixit, Jakhar and Kumar (2022), the adoption of Industry 4.0 is investigated through the role of innovation capabilities to achieve lean and sustainable manufacturing criteria. The conceptual model constructed that linked LM principles and DT technologies and associated hypothesis are tested through Structural Equation Modelling (SEM). This methodology is frequently used in the relationship between LM principles, DT technologies and sustainability. In the study by Varela *et al.* (2019) the relationship between LM principles and Industry 4.0's impact to sustainability individually, through constructing a conceptual model and testing the hypothesis through Structural Equation Modelling (SEM). This is like current research in terms of validating the conceptual model, although individual relationships are examined for sustainability. Another study that had sustainability focus was the research by Qureshi *et al.* (2023) where LM and Industry 4.0 within sustainable supply chains are analysed. Furthermore, Kamble *et al.* (2020) collected quantitative data from 225 managers to link LM and Industry 4.0 in Indian manufacturing companies for sustainable operational performance. The data collected is later analysed using SEM. In an example other than sustainability, Tortorella, Miorando and Cawley (2019) focused on the moderating role of LM principles for adoption of DT technologies for operational performance improvement using quantitative research methodology and analysed by SEM.

Authors	Overview of the research and methodology	Quantitative Method	Data Analysis
(Dixit, Jakhar and Kumar, 2022)	The research examined the role of innovation capabilities on Industry 4.0 for lean and sustainable manufacturing	Survey Questionnaire	Structural Equation Modelling
(Qureshi *et al.*, 2023)	The study focused on Lean Manufacturing for Industry 4.0 towards sustainable supply chain	Survey Questionnaire	Structural Equation Modelling
(Kamble *et al.*, 2020)	This study examined the effects of Industry 4.0 and LM to sustainable operational performance	Survey Questionnaire	Structural Equation Modelling
(Varela *et al.*, 2019)	This research investigated the relationship between LM, Industry 4.0 and sustainability criteria	Survey Questionnaire	Structural Equation Modelling
(Tortorella, Miorando and Cawley, 2019)	The focus of the research is examining moderating role of LM principles for adoption of DT	Survey Questionnaire	Structural Equation Modelling

Table 4.4 Review of literature adopting quantitative research methodology

4.5. Research Design

The research strategy refers to the plan how a researcher intends to address the research question (Saunders, Lewis and Thornhill, 2012). A common research strategy involving conducting quantitative research includes survey questionnaire. Aligned with common literature, this research adopts questionnaire, and research design is shown in Fig. 4.5. The research process and the rationale for adopting them for this study will be explained.

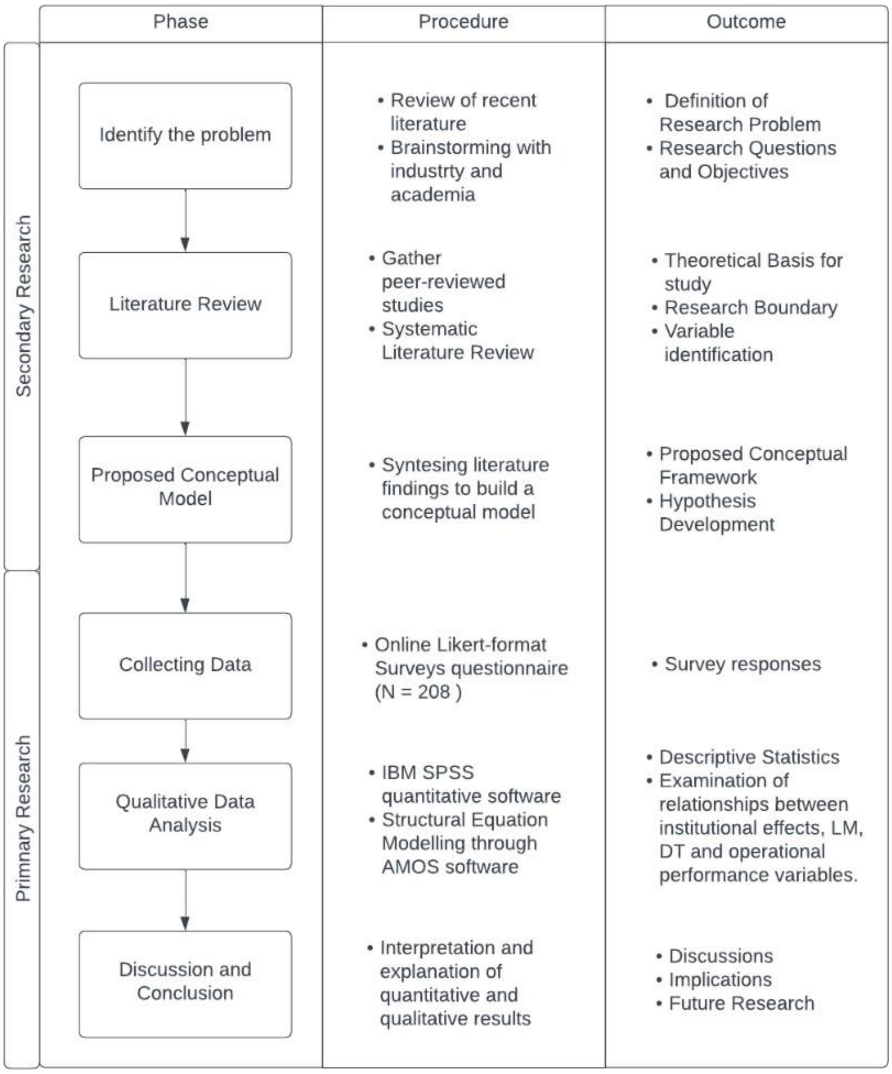


Figure 4.1 Schematic diagram of research design

The research design, as illustrated in Figure 4.1, adopts a systematic and structured approach to guide the research process. The research process starts with identification of the problem through review of recent literature. Additionally, discussions with academics and industry professionals in the manufacturing sector are conducted to further refine the research problem and set clear objectives. Following the alignment with the defined research problem, a comprehensive, in-depth literature review is carried out. As part of this PhD thesis, a systematic literature review has been completed and published (Yilmaz *et al.*, 2022). The literature review has structured the theoretical foundation for the study and defined the key variables for LM principles, DT technologies as explained in Chapter 2. Using the literature review, a conceptual framework is proposed together with the associated hypotheses to guide the research process. The conceptual framework generation and theoretical development have been highlighted in Chapter 3 of this study.

To empirically validate the conceptual framework and test the hypothesis, next stage involves data collection and analysis. The data collection is completed through survey questionnaire with total of 208 participants. This method allowed collection of quantitative data that can be used for statistical analysis. Upon collecting the data, statistical analysis and empirical validation of the conceptual model is completed through IBM SPSS. Furthermore, AMOS software is used to complete Structural Equation Modelling (SEM). This analysis investigates the connections between institutional effects, LM principles, DT technologies, and operational performance as specified in the conceptual model. The outcomes of this quantitative analysis are explored in the following section, which details the testing of hypotheses and presents the key findings. The conclusion emphasizes the implications, contributions to the field of research, and suggestions for future studies. Up to this point, the literature review, conceptual model, and methodology have been discussed in Chapters 1 to 4. Moving forward, data collection and analysis will be explained. In the next section the chosen method of data collection, the survey questionnaire, will be described next, along with a detailed account of how the data was gathered. Subsequently, a comprehensive explanation of the data analysis process will be provided, including details on the statistical analysis and structural equation modelling.

4.6. Survey Development

The chosen method of data collection is through the survey questionnaire that will be explained below with questionnaire development, administration, and sampling. The questionnaire development process begins with the selection of the questionnaire type and format, focusing on the ways of data collection. Additionally, the content of each question is carefully developed, with considerations for how questions are constructed and the sequence in which they appear in the questionnaire. The type of responses allowed by the questionnaire is also determined, ensuring they align with the methodology. After the questionnaire has been developed, it undergoes pilot with a target group to evaluate the effectiveness of the questions to meet the aim. Feedback from this pilot is used to make necessary revisions, enhancing the reliability and validity of the questionnaire. Once revised, the questionnaire is then administered to the selected sample. In the next section, the development phase will be discussed in detail, starting with the selection of the questionnaire type and format, and moving through each subsequent stage of its development.

After assessing the questionnaire survey as an option, next steps involve constructing a questionnaire type and format. There are 4 major survey methods that are mailed questionnaires, internet surveys, telephone and face-to-face interviews (Czaja and Blair, 2005; Saunders, Lewis and Thornhill, 2012). In this study, internet surveys were chosen as the data collection method. One of the important research gaps identified in Section 2.4.1. was lack of large sample and inability to perform statistical analysis. To fill this void in research, a sample of at least 150 respondents are aimed and large sample size is more suitable for internet questionnaires as it offers range of benefits such as automated data input, broader outreach through social media and enables access to respondents regardless of their location (Sammut, Griscti and Norman, 2021). An essential aspect of utilizing an internet survey is its compatibility with closed-ended questions, which need to be designed as simple and engaging for the respondents (Saunders, Lewis and Thornhill, 2012). Due to the expansive scope of LM principles and DT technologies, it is essential to maintain a simple and consistent sequence for respondents. Therefore, to ensure consistency and simplicity, the questionnaire includes only closed-end questions.

The content of the questionnaire is based on the conceptual model presented in Chapter 4 which is a result of extensive literature review. The summary outlining the information of construct, and each component are displayed in Table 4.5 below. Each of the construct and component was presented in the questionnaire. There are three methodologies for generating questions that are using questions from existing surveys, adapting these pre-existing questions to suit specific needs, and creating entirely new questions developing own questions (Saunders, Lewis and Thornhill, 2012).

Construct	Content of Each Construct	Components
Institutional Effects	Section 3.3	Table 3.4
Lean Manufacturing Principles	Section 3.3	Table 2.8
Digital Transformation Technologies	Section 3.3	Table 2.5
Operational Performance	Section 3.3	Table 2.6

Table 4.5 Content of each questionnaire section

The measurement items are shown in the Table 4.6. The questions considered for institutional effects, the questions are adapted from Gupta *et al.*, (2020), which reported Cronbach's alpha values above 0.80 and above for all institutional pressure constructs, composite reliability between 0.88 and 0.896, and AVE values above 0.50, confirming convergent validity and supporting their use in the survey. The adaptations were tailored to align with the scope of this research and external factors specific to Turkey, as institutional theories emphasize the influence of external factors within specific locations. This approach ensures that the measurement items are contextually relevant representative of geographical setting.

For LM and DT measurement items, questions are mostly adapted from other questionnaires or generated from literature (Garza-Reyes, 2015; Tortorella and Fettermann, 2018; Kamble *et al.*, 2020). In these studies, reliability was established through Cronbach's alpha values exceeding the 0.70 threshold, and construct validity was confirmed via confirmatory factor analysis, indicating that the scales accurately capture the intended dimensions of LM principles and DT technologies. Similarly, measurement items for Operational Performance also demonstrated Cronbach's alpha values consistently above 0.70 for each construct, reflecting high internal consistency, with confirmatory factor analysis results further supporting both convergent and discriminant validity for all items (Tortorella, Giglio and van Dun, 2019; Calabrese, Levialdi Ghiron and Tiburzi, 2021).

Since the aim of the study is to develop a comprehensive model, multiple studies have been referenced, and detailed explanations for each component are provided in Table 4.7. The order of the questions was primarily informed by the conceptual model while also considering the structure of existing questionnaires to ensure consistency and relevance.

Construct	**Component**	**Item Code**	**Content Summary**	**References**
Institutional Effects	Mimetic Pressures (MP)	IE1	Table 3.3	(Gupta *et al.*, 2020)
		IE2		
	Normative Pressures (NP)	IE3		
		IE4		
	Coercive Pressures	IE5		
		IE6		
Lean Manufacturing Principles	Eliminate Waste	LM1	Table 2.8	(Garza-Reyes, 2015; Tortorella and Fettermann, 2018)
		LM2		
	Built-in Quality	LM3		
		LM4		

	Kanban	LM5		
		LM6		
	Standard Work	LM7		
	Continuous Improvement	LM8		
		LM9		
	People & Teamwork	LM10		
		LM11		
Digital Transformation Technologies	Simulation & Digital Twin	DT1	Table 2.5	(Kamble *et al.*, 2020)
		DT2		
	Big Data	DT3		
		DT4		
	Robotics & Automation	DT5		
		DT6		
	Cloud Computing	DT7		
	Cyber-physical Systems	DT8		
	Internet-of-Things	DT9		
	Artificial Intelligence	DT10		
	Additive Manufacturing	DT11		
Operational Performance	Inventory	OP1	Table 2.6	(Tortorella, Giglio and van Dun, 2019; Calabrese, Levialdi Ghiron and Tiburzi, 2021)
	Productivity	OP2		
	Lead-time	OP3		
	Quality	OP4		
	Profitability	OP5		
	Cost	OP6		

Table 4.6 Overview of research constructs and their measurement scales

In this research Likert-style questions are used to collect the relevant data from responders. As for the form of response, Likert-style rating is one of the most popular metric scales that allow quantitative data collection where it measures opinions (Saunders, Lewis and Thornhill, 2012). For each measurement item, an intensity scale is used to express agreement or disagreement. A common Likert scale a five-point scale where respondents assess a statement. On this scale, choosing 1 generally signifies strong disagreement, while selecting 5 indicates strong agreement-testing (Hair Jr., Page and Brunsveld, 2019).

4.6.1. Pre-testing

Through completing the previous steps of questionnaire development in terms of content, sequence, layout and form of response, a survey is prepared for pilot. This pilot test is important to make sure that the questions are coherent and correctly understood in the context. Furthermore, it gives an assessment on the validity and reliability of the data aimed to be collected (Saunders, Lewis and Thornhill, 2012). For the pilot study, two academics specializing in operational management at Brunel University and 15 industrial professionals in Turkish SMEs were engaged, fulfilling the minimum requirement that is 10 (Fink, 2016). All the industrial professionals were part of the survey's target group, being directly involved in internal manufacturing operations. Their roles encompassed positions such as manufacturing engineers, quality managers, and mechanical engineers, ensuring their feedback was relevant.

The pilot involved 15 industry professionals, all native Turkish speakers, who were presented with both English and Turkish translations of the survey. Short interviews, lasting 10 to 30 minutes, were conducted with the participants to refine the questions and wording. These interviews aimed to ensure that the translations, terms, and context were correctly understood by respondents. One of the key considerations was ensuring the accuracy of the Turkish translations for the target audience. As the targeted survey respondents were native Turkish speakers, but the original questions and much of the supporting literature were developed in English, there was a potential for translation errors and typographical mistakes. To address this, careful revisions were made to ensure that the translations were precise and conveyed the intended meaning accurately, minimizing the risk of misinterpretation by the respondents.

In terms of terminology, LM principles often include specialized jargon such as “Kanban” which may not be easily understood by all respondents. Based on feedback from the pilot testing, these terms were either clarified or replaced with simpler, more practical explanations to ensure participants could understand them. For example, instead of directly using the term “Kanban” it was explained as a method for classifying groups and utilizing signals, cards, or tickets from preceding process. Another refinement involved questions on institutional effects, particularly those referencing government adoption of DT technologies. Feedback from 10 out of 15 respondents highlighted the importance of explicitly mentioning “KOSGEB” alongside “government” as KOSGEB is a key government organization supporting SMEs in Turkey. Incorporating this feedback ensured the questions were more contextually relevant and comprehensible for the target audience. Hence, based on the feedback received during the pilot test process, the necessary refinements were implemented to ensure the questions were clear, contextually relevant, and effectively tailored to the understanding and needs of the target audience.

4.6.2. Questionnaire Administration

After completing the pilot testing and adapting the questionnaire based on feedback, the next stage involved questionnaire administration. The survey was primarily distributed through social media channels, specifically Facebook and LinkedIn, where the target population is most active. Social media groups that promote KOSGEB support initiatives were also utilized to reach a broader audience within the target demographic. In addition to social media outreach, the researcher directly contacted engineers and management personnel from SMEs who were known to them, encouraging their participation in completing the survey. This comprehensive distribution strategy ensured extensive reach within the population. As a result, the questionnaire was distributed to a total of 1,023 individuals, yielding 278 completed responses.

4.6.3. Non-response Bias

Following the survey administration, a significant percentage of non-responders was observed. To address potential non-response bias, it was necessary to examine whether the characteristics of respondents differed significantly from those of non-responders so a common method for evaluating non-response bias, wave analysis, was employed (Armstrong and Overton, 1977). Wave analysis involves checking the first wave of answers to second wave where first wave of answers which comprises 52% of the population, to the subsequent wave, accounting for the remaining 48%. A t-test was conducted to compare the two waves based on key variables such as industry and company size. The results indicated no statistical difference between the two groups, with a high t-value and a p-value lower than 0.05, suggesting no significant variation in their characteristics. Based on this finding, the results were considered representative of the target population as non-response bias is not substantial enough to affect the validity of the study's conclusions.

4.7. Sampling

The aim of sampling is to pick the correct people that can provide the desired information for the research. Hence it is important to state the targeted population and context of the research firstly. This research investigates manufacturing SMEs in Turkey where the SME definition is given by European Commission (2021). The targeted respondents are employees working in manufacturing SMEs, particularly those involved in manufacturing operations, as well as the design and quality functions of a product. Specifically, the sample includes top and middle management professionals and engineers who possess knowledge and experience in LM principles and DT technologies. The SMEs in this study were identified through publicly available registries of organized industrial zones and industry databases, with inclusion criteria requiring active manufacturing operations and compliance with the SME size definition set by the European Commission, thereby ensuring accurate identification of eligible firms.

In terms of sampling techniques there are two options that are called probability and non-probability sampling. In probability sampling, every respondent in the target population is known and a chance with being selected, where non-probability sampling does not provide a chance to be selected (Daniel, 2012). For survey-based online questionnaires, probability sampling is the more commonly used technique where every person part of the targeted population has a chance of being selected through online survey (Cumming, 1990; Hibberts, Johnson and Hudson, 2012). This study adopts random sampling, a widely used probability sampling method which involves selecting representative subsets from a larger dataset to ensure that every individual in the target population has an equal chance of selection (Mahmud *et al.*, 2020). By doing so, random sampling enhances the supports efficient data analysis, and aligns with the study's objective of achieving unbiased and generalizable results. Generalisability is ensured by diversifying the sample across various manufacturing sectors and production types, enabling the findings to capture the variability of DT adoption in Turkish SMEs. The sample is then compared with official data from the Turkish Statistical Institute (TÜİK, 2023) on the overall SME population by sector and size to confirm its alignment with the broader SME population.

In terms of sample size, this study aimed employ Structural Equation Modelling (SEM) and requires sufficient quantitative data to meet the sample size requirements for robust analysis. Research has indicated that a minimum sample size of 100 is necessary for SEM, with 150–200 being recognized as medium (Kyriazos, 2018) Ideally, a sample size above 200 is preferred, as larger samples reduce the influence of standard deviation and increase the stability of parameter estimates (Jackson, 2001). However, there has been no clear instructions and studies have shown that there is no "one-size-fits all" approach (Wolf *et al.*, 2013). Elements like research design, construct relationships, data reliability, and the number of survey questions can influence sample size requirements and a common guideline is a participant-to-question ratio of 5:1 (Tanaka, 1987; Kyriazos, 2018). With 34 questions in this study, this ratio suggests a minimum of 170 participants. In alignment with these recommendations, this research has established a target minimum sample size of 200 which ensures adequate sample size for effective SEM analysis while accounting for the study's design and measurement requirements.

A frame is used to identify the members of the population for the research and a sampling frame is a list of complete population that is identified by this frame (Blair and Blair, 2015). KOSGEB, the Turkish Small and Medium Enterprises Development Organization, maintains a website that features SMEs in Turkey and serves as a valuable resource for identifying SMEs in Turkey (KOSGEB, 2023c). Furthermore, there are social media groups where the members are SME employees that track KOSGEB initiatives and support. Hence, sample frame can be reached from these sources. Ensuring that SMEs in the sampling frame meet size requirements, are well represented across sectors, and maintain active manufacturing operations helps the study to maintain relevance research question and strengthens the credibility of its findings. To determine the sampling frame, the expected sample size and response rate must be considered where a common approach involves multiplying the desired sample size by the anticipated response rate to ensure the required sample size is achieved (Bryman and Bell, 2011). In line with the research topic, the response rate can be investigated in the field of operational management. Research analysing 233 survey research in operations management showed that an average response rate is 32.2% (Frohlich, 2002). However, more recent studies have shown varying response rates, typically ranging between 19–23% (Krell, Matook and Rohde, 2016; Tortorella, Narayanamurthy and Thurer, 2021; Rossini *et al.*, 2022). In line with these findings, Klassen and Jacobs (2001) argued that the researchers need to adjust their expectations up to 20%. To be on the safe side, this research has aimed for %20 response rate to make sure the minimum sample rate is reached. Based on this, the sampling frame needs to include at least 1,000 individuals to achieve the required sample size for robust and reliable data analysis.

4.8. Data Analysis

After data is collected, analysis is carried out using two software: IBM SPSS and AMOS. The initial analysis involves assessing the demographics of the sample population to ensure it mirrors the target population. This includes conducting tests for normality in SPSS to determine if the data distribution is normal. The analysis also covers checking data reliability and validity. Subsequently, Exploratory Factor Analysis (EVA) is conducted to verify if the data aligns with the hypothesized model structure. This is followed by Confirmatory Factor Analysis which primarily evaluates the reliability and validity of the constructs. The final analytical step involves Structural Equation Modelling (SEM).

After the data is collected through the questionnaire survey the first step is preliminary data analysis. This includes removing incomplete responses, duplicates, and outliers. Additionally, the demographics of the respondents are examined, focusing on aspects such as company size, revenue, and sector. Based on the SME criteria outlined in Chapter 2 by European Comission (2021), this information is utilized to exclude companies from the study that do not qualify as SMEs. More specifically the ones that are large enterprises with higher revenue and larger size. After the data processing up, the demographics are reviewed to assess whether the sample the accurately represents the SME population. This step ensures that the collected data aligns with the study's objectives and supports reliable and generalizable findings.

Next, normality test is competed to determine whether the data is normally distributed. The test has two parts: skewness, which assesses the symmetry of the distribution, and kurtosis, which examines the peakedness of the distribution (Tabachnick and Fidell, 2018). These tests are done through Descriptive Statics function in SPSS software. After establishing the normality, the next stage examining data reliability and validity. Data reliability relates to internal consistency reflects the degree to which items on a scale measure the same underlying attribute and it is typically assessed using Cronbach's coefficient alpha, with higher values indicating greater reliability (Pallant, 2020). Steps to analyse data reliability ensures integrity of the collected data to make sure there is a foundation for meaningful statistical analysis.

Data validity examines the scale how well the scale measures what it is intended to measure. Although there is no single definitive indicator of a scale's validity, where main types of validity are content and construct validity (Pallant, 2020). Content validity indicates how well the measurement questions are relevant and representative of the targeted construct for a specific assessment purpose (Almanasreh, Moles and Chen, 2019). It is established through a review of the literature, incorporating questions from previous studies, and conducting pilot tests where respondents provide feedback on the content to evaluate its validity. Construct validity assesses how accurately a scale measures a theoretical concept by investigating its connections with related constructs for convergent validity and unrelated constructs for discriminant validity (Pallant, 2020). In this research convergent validity is examined through Explanatory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) whereas discriminant validity is investigated through EFA and Average Variance Extracted (EVA).

4.8.1.1. Exploratory Factor Analysis (EFA) & Confirmatory Factor Analysis (CFA)

EFA is a statistical method used to identify underlying factors that explain the relationships and structure among a set of observed variables (Watkins, 2018). EFA is utilized for data pre-processing and evaluating measurement items, offering statistical assessment to either corroborate or refute the relationships proposed in the conceptual model. It is conducted through IBM SPSS software, and it is completed through KMO and Bartlett's and this is followed by assessment of Total Variance Explained and Scree Plot (Shrestha, 2021). Finally, factor patterns are assessed in line with the conceptual model proposed.

EFA is conducted early stages of the research to examine the relationship between the variables, where there is no preconceived hypothesis about the underlying structure. Following EFA, CFA is used to test specific hypotheses about the structure of these variables, using a clear theory or model beforehand (Pallant, 2020). CFA is conducted through using AMOS 29 software. The results of CFA are evaluated through a set of goodness of fit (GOF) index scores. A comparison between the GOF index and CFA results are made to establish CFA. Using CFA results, convergent validity is established through Average Variance Extracted (AVE) and Composite Reliability (CR) and discriminant validity is assessed using the Fornell-Larcker criterion (Fornell and Larcker, 1981). An overall summary is provided to check EFA and CFA results to check whether data validity test are completed.

4.8.1.2. Structural Equation Modelling (SEM)

After data validity tests are completed and the measurement model shows good fit index, Structural Equation Modelling is completed through AMOS software. SEM is a theory-driven approach to data analysis that evaluates hypothesized causal relationships between variables, as specified by the conceptual model (Mueller and Hancock, 2018). Using AMOS software, the relationships between IE, LM principles, DT technologies and operational performance variables are analysed. The suitability of the model is evaluated by applying Goodness of Fit (GOF) indices, which allows to check whether the model meets the predefined thresholds required for an adequate fit. This is followed by the assessment of path coefficients that convey the strength and direction of relationship between the variables. Finally, hypothesis testing is performed for each proposed hypothesis to show which relationships are statistically significant and which are not. This approach allows a thorough validation of the theoretical framework proposed in the research. The results of SEM are interpreted in the Discussion in Chapter 6.

4.8.1.3. IBM SPSS and AMOS Software

This research utilizes IBM SPSS for statistical analysis and IBM SPSS AMOS 29 software for SEM as provided by Brunel University to complete SEM. More specifically SPSS short for Statistical Product and Service Solutions, is a software designed for analysing data in the social sciences and it is popular due to its flexibility in data formats, its extensive tools for data transformation and file management, and its broad range of statistical analysis techniques (Ho, 2006). Furthermore, AMOS is short for Analysis of Moment Structures, and it allows users to create, observe and adjust their models graphically with drawing tools for SEM (Arbuckle, 2019). One of the primary reasons for selecting this tool was its user-friendliness and ease of use, which offer practicality and convenience. Additionally, availability played a crucial role, as both SPSS and AMOS Software are accessible through Brunel University.

4.9. Time Horizon

For this research time horizon is cross-sectional design, where a study is completed at a brief period or in a single instance (Levin, 2006). According to Saunders, Lewis and Thornhill (2012) the most common methods of data collection associated with cross-sectional design are surveys. In contrast, longitudinal studies, which track changes over time, were not feasible for this PhD study due to time constraints. The practical necessity of completing data collection within the PhD timeline ruled out the possibility of adopting a longitudinal approach where the schematic diagram of the research design is displayed in Figure 4.5. Hence, this research adopts a cross-sectional design, as it aligns with the study's methodological framework and is consistent with the overall research design.

4.10. Ethical Considerations

Ethics refers to o the standards of behaviour that guide researchers in conducting their work responsibly and respecting the rights of their subjects (Saunders, Lewis and Thornhill, 2012). Business researchers often follow evolving ethical guidelines from multiple sources according to their research, including their own institutions (Cassell, Cunliffe and Grandy, 2018). This research complies the ethical guidelines set out by Brunel University and necessary approvals were obtained prior to conducting the study, providing a structured framework for addressing ethical considerations. One of the fundamental principles of ethics is informed consent and participants' right to privacy (Hair Jr., Page, and Brunsveld, 2019). To fulfil these ethical obligations, participants were provided with an introductory letter and a consent form, as shown in Appendix B.

Aligned with this, Collis and Hussey (2014) highlight the importance of anonymity, voluntary participation, and confidentiality in research ethics. For this study, data was collected anonymously through an online questionnaire, ensuring that participants could not identified to that ensured privacy. The participation in the survey was voluntary allowing individuals to decide freely whether to contribute to the research. These introductory letters outlined key details about the research, ensuring participants were adequately informed about the research before getting involved. By providing this information prior, the research ensured transparency and helped participants make an informed decision about their involvement. By adhering to these ethical principles and leveraging the anonymous nature of the online questionnaire, the research ensured that participants privacy and confidentiality are respected throughout the study.

4.11. Chapter Conclusion

This chapter provides a comprehensive overview of the methodology used to achieve the research objectives and answer the research questions for this study. Firstly, the research philosophy is explained, adopting a positivism and deductive approach, grounded in realism ontology. Following the philosophical underpinnings, the research choices are discussed, emphasizing the suitability of quantitative methods for this study. The research design is introduced, with survey questionnaires selected as the primary research method and SEM identified for data analysis. The development of the questionnaire is detailed, covering aspects such as content, sequence of questions, and layout. The process of pilot testing and the subsequent administration of the questionnaire is also explained. The chapter then introduces and provides an in-depth explanation of how the data analysis is structured and planned to be conducted. Finally, the chapter concludes with a discussion of ethical considerations which aligns with the ethical guidelines of Brunel University. Following the introduction of the research methodology, the next section focuses on the collected data and its analysis.

Chapter 5: Findings of Quantitative Research

5.1. Chapter Introduction

The previous chapter presented the methodology for this study, which is quantitative research through survey supported with SEM for data analysis. Once the data collection is complete, the initial analysis is conducted using IBM SPSS Statistics 29. More specifically, in preliminary data analysis with demographics, data normality, validity and reliability tests are conducted. These are followed by Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to analyse the measurement and structure of the model, respectively. Structural Equation Modelling (SEM) is used through IBM AMOS 29 software to validate and test the performance of the conceptual model and test the associated hypothesis, proposed in Chapter 3.

5.2. Data Analysis

The questionnaire survey was sent out to 1,123 people who were Manufacturing SMEs in Turkey, and 278 responses were received. After receiving the results, preliminary data processing was completed to ensure no missing, isolated, or duplicate date are included in the study. Out of 278 respondents, 208 of the responses were suitable where the details are displayed in Table 5.1.

Total Responses	278
Duplicate, isolate, incomplete responses	-28
Respondents are not classified as SME	-48
Total included	**208**

Table 5.1 Results of preliminary data processing

Out of 278 responses, 28 of responses are removed due to being duplicate or incomplete responses. 32 of the responses are removed because they originate from respondents employed at large enterprises according to the criteria outlined in Chapter 2, with an annual revenue exceeding 2 million euros or a workforce surpassing 250 employees. Consequently, 208 responses are deemed suitable and retained for the subsequent data analysis. Following this, data preliminary data processing, demographics of the respondents are analysed below.

5.3. Demographic Profile of Respondents

As initial step of data analysis demographic profile of the respondents is analysed focusing on the employee count, position, sector, and annual turnover. The breakdown of this data is shown in the Table 5.2 below.

Employee Count	No of Companies	%
≤ 10	26	12.5%
≤ 50	59	28.4%
≤ 100	61	29.3%
≤ 250	62	29.8%
Position	No of Companies	%
CEO	15	8.9%
Manufacturing Engineer	110	65.5%
Mechanical Engineer	32	18.5%
Quality Engineer	51	30.4%
Sector	No of Companies	%
Chemical, Medicine	12	5.8%
Food and Drinks	28	13.5%
Glass	6	2.9%
Machinery, Automotive, Aerospace	38	18.3%
Metal and Metalworking	27	17.8%
Plastic	37	6.7%
Textile	14	16.8%
Wood, Paper	35	13.0%
Other	11	5.3%
Production Type	No of Companies	%
Batch	89	53.0%
Continuous	80	47.6%
Job Shop	39	23.2%
Annual Turnover	No of Companies	%
≤ 2	45	26.8%
≤ 10	84	50.0%

≤ 50	79	46.4%

Table 5.2 Demographic profile of the survey respondents (n=208)

The demographic profile of the respondents is analysed to show that the sample size reflects the population of manufacturing SMEs in next section.

5.3.1. Demographic Profile by Sector and Production Type

According to Table 5.2, the demographic profile indicates that the respondents come from a diverse range of industries, with a higher concentration of respondents from the Machinery, Automotive, Aerospace (18.3%), Metal and Metalworking (17.8%), and Textile (16.8%) sectors. Comparing these figures with the national statistics on manufacturing SMEs in Turkey from TÜİK (2023) shown in Table 5.3, most of the workforce in manufacturing SMEs is similarly employed in these three sectors, where Textile (19.4%), Metal and Metalworking (20.4%), and Machinery, Automotive, Aerospace (18.2%) account for the largest proportions. The survey data also reflects representation in sectors such as Food and Drinks (13.5%), Chemical and Medicine (5.8%), and Plastic (6.7%), contributing to the diversity of industries represented by Turkish SMEs. Overall, the survey data captures the diversity within the manufacturing SMEs in Turkey and aligns closely with the national statistics, indicating that the survey data is a strong representation of the targeted demographic.

Sector	Survey (%)	Turkey SME (%)
Chemical, Medicine	5.8%	7.3 %
Food and Drinks	13.5%	12.7 %
Glass	2.9%	5.4 %
Machinery, Automotive, Aerospace	18.3%	18.2 %
Metal and Metalworking	17.8%	20.4 %
Plastic	6.7%	7.3 %
Textile	16.8%	19.4 %
Wood, Paper	13.0%	7.3 %
Other	5.3%	2%

Table 5.3 Comparison of Sector Representation Survey vs. Industry Data from TÜİK (2023)

Most of the respondents worked in Manufacturing Department at 65.5% followed by Quality departments at 30,5% Mechanical Engineering Department at 18,5%. Only 9% of the respondents came from senior and management positions. In terms of production type, there is almost an even split where batch and continuous production where batch production accounts as the most common production type with 53%, followed by continuous production with 47,6%. Job Shop production was less common with 23,2%. Hence, the survey data captures a range of production types that is reflective of the diverse sectors represented within the dataset, showcasing the spectrum of production methods across the sectors.

5.3.2. Company Size and Job Designation of Respondents

As explained in Chapter 2, to be classified as an SME, companies must meet specific criteria in annual turnover and staff count. Reflecting these criteria, Table 5.4 illustrates the company size distribution among the survey's respondents It shows that among 208 respondents: 50.5% are medium, 37.5% small, and 12% micro-sized companies.

Company Type	No of Companies	%
Medium	105	50,5%
Small	78	37,5%
Micro	25	12,0%
Total	208	1%

Table 5.4 Company type of survey respondents (n=208)

This aligns with KOSGEB’s 2022 data on Turkish SMEs in manufacturing sector, where medium-sized companies account for 48,9% of the SMEs workforce (KOSGEB, 2022). Additionally, survey reflects significant representation from small-sized companies at 37,5% and micro companies at 12%. This is again parallel to the workforce distribution in Turkish SMEs in manufacturing sector where small and micro-sized companies represent 28,5% and 22,6% of total SME workforce. Overall, the similarities between the SME workforce statistics to the survey data shows that survey’s respondents encapsulate composition of Turkish SME sector.

5.4. Normality Test

To assess whether the data is normally distributed, descriptive statistics was carried on SPSS which provides information on how the data is distributed. Through descriptive statistics, Kurtosis and Skewness are displayed representing the symmetry and 'peakedness' of distribution, respectively. In an unlikely case of ultimate normal distribution, kurtosis and skewness would be (Pallant, 2020).

Constructs	N	Mean	Std. Deviation	Variance	Skewness	Kurtosis
IE	208	3.627	0.535	0.286	-0.905	1.368
LM	208	3.798	0.539	0.291	-0.702	0.297
DT	208	3.307	0.695	0.483	-0.590	-0.041
OP	208	3.716	0.622	0.387	-0.971	1.491
Valid	208					

Table 5.5. Descriptive Statistics for all constructs (n=208)

According to George and Mallery (2010), the acceptable levels to pass normality test is having a skewness and kurtosis values between 2 and -2. As displayed in Table 5.5, the Skewness and Kurtosis variables are in range between 2 and -2, which adheres to the criteria for normal distribution.

5.5. Data Validity and Reliability Assessment

Upon establishing that the data is normally distributed next stage is to check validity and reliability of data to be used in the study.

5.5.1. Reliability Assessment

Reliability is related to internal consistency of the data. It shows how robust a questionnaire is to achieving consistent findings when it is done repeatedly (Saunders, Lewis and Thornhill, 2012). The conventional method of assessing internal reliability is through Cronbach's Alpha (α). The values of Cronbach's Alpha (α) range between 0-1. The higher values show higher consistency where the values between 0.7-0.9 are acceptable to be used in advanced level of research (Hair, Ringle and Sarstedt, 2011). Cronbach's Alpha of each construct of this study is conveyed in Table 5.6 below.

Constructs	Items	Cronbach's Alpha
IE	6	0.887
LM	11	0.942
DT	11	0.957
OP	6	0.927

Table 5.6 Cronbach's Alpha for all constructs

The Cronbach Alpha of LM, DT and OP performance are all above 0.8 benchmarks indicating excellent reliability. However, the value of IE representing Institutional Effects shows just on the threshold at 0.704. This is still acceptable as when the measured items are below 10, Cronbach Alpha tends to underestimate the value of consistency and a value between 0.7-0.77 is still considered relatively high (Taber, 2018). Overall, the data shows that there is high level of reliability of measurement items.

5.5.2. Data Validity

There are two primary ways to check the quality of data according to Saunders, Lewis and Thornhill (2012) that are checking reliability and validity. Furthermore, in previous section data reliability was analysed. he methodology and checks for data validity are outlined in Table 5.7 below, as a guideline for the data analysis process, which will be elaborated in upcoming sections. It incorporates content and construct validity which further divides into discriminant and convergent validity. Content validity is often derived from literature reviews and reinforced through pilot testing. Additionally, one of the common ways to test for validity is to use CFA, as its examination of relationships within the model (Byrne, 2001).

Validity Concept	**Definitions**	**Test Method in this study**
Content validity	It provides examination to check the degree to which questions in the questionnaire offer sufficient representation of the research question (Saunders, Lewis and Thornhill, 2012)	This is validated through extensive literature review. The items of questionnaire are collected from previous studies where content validity is confirmed. Further pilot study on

		experts and potential respondents are also a contributor.
Construct validity	It relates to the degree to which the measurement items in a study accurately and meaningfully capture the concepts they are designed to represent (Saunders, Lewis and Thornhill, 2012)	The assessment is made through discriminant and convergent validity.
Discriminant Validity	This refers to the capacity of a measurement items to distinguish between two distinct, yet related, constructs (Ruel *et al.*, 2021)	It is done through CFA and the average variance extracted (AVE) should be higher than 0.50 (Hair, Ringle and Sarstedt, 2011)
Convergent Validity	It shows the degree to which different measurement methods and scale items are consistent and coherent in indicating a single underlying construct (Ruel *et al.*, 2021)	This is tested through explanatory factor analysis (EFA) followed by confirmatory factor analysis (CFA).

Table 5.7 Data validity checks for the research

5.6. Exploratory Factor Analysis (EFA)

Explanatory Factor Analysis (EFA) is used to investigate correlative relationships among manifest measurement items and model them assuming a causal link in a common factor (Goretzko, Pham and Bühner, 2021). Through SPSS software, a range of factor models from one-to-many factors can be produced, and through rotation, the interpretability of the retained factors is enhanced by modifying the initial solution according to different statistical criteria specific to the selected method (Kline, 2016). Since the measurement items are gathered from prior studies and not tested in one study, conducting EFA and assessing their suitability and coherence is necessary.

Prior to EFA, it is important to assess whether the data set is suitable for factorability through statistical measures called Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity (Pallant, 2020). KMO assesses the adequacy of distribution of values (Ho, 2006) and Bartlett's Test is to check variables are sufficiently correlated, deviating notably from the identity matrix, indicating they are not orthogonal (Shrestha, 2021). This can be carried out through SPSS, and it was carried out for this study as shown in Table 5.8.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.905
Bartlett's Test of Sphericity	Approx. Chi-Square	3084.618
	df	561
	Sig.	.000

Table 5.8 KMO and Bartlett's Test

According to Kaiser *et al.* (2019), higher the KMO measure, more suitable the data set to factorability where the values above 0.8 are considered suitable to be used. As the KMO value is 0.905, the KMO test is sufficiently satisfied. For Bartlett's Test of Sphericity, the acceptable value is (p<0.05), where the test shows the value is lower (Hair, Black and Babin, 2010). Both KMO and Bartlett's test results show that the data set is suitable for factor analysis.

The Total Variance Explained in Table 5.9 from SPSS reveals four factors with eigenvalues exceeding 1, accounting for over 57.513% of the total variance. The analysis in SPSS is completed on default procedure instead of selecting a specific number of factors.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.228	35.965	35.965	11.706	34.429	34.429	6.479	19.056	19.056
2	3.741	11.004	46.968	3.333	9.802	44.231	5.757	16.933	35.989
3	3.024	8.895	55.863	2.696	7.928	52.159	3.757	11.050	47.039
4	2.204	6.481	62.344	1.821	5.355	57.514	3.562	10.475	57.514
5	.914	2.687	65.031						
6	.841	2.474	67.505						
7	.762	2.242	69.747						

Table 5.9 EFA Rotated Matrix of items loadings on the constructs

Correspondingly, the Scree Plot at Figure 5.1. shows the 'elbow' occurring at the fourth factor. More specifically, at the ‘elbow’ of the scree plot, slope of the curve changes direction conveying optimal factors to include int the study. Overall, the pattern of four factors aligns with the four constructs outlined in the research.

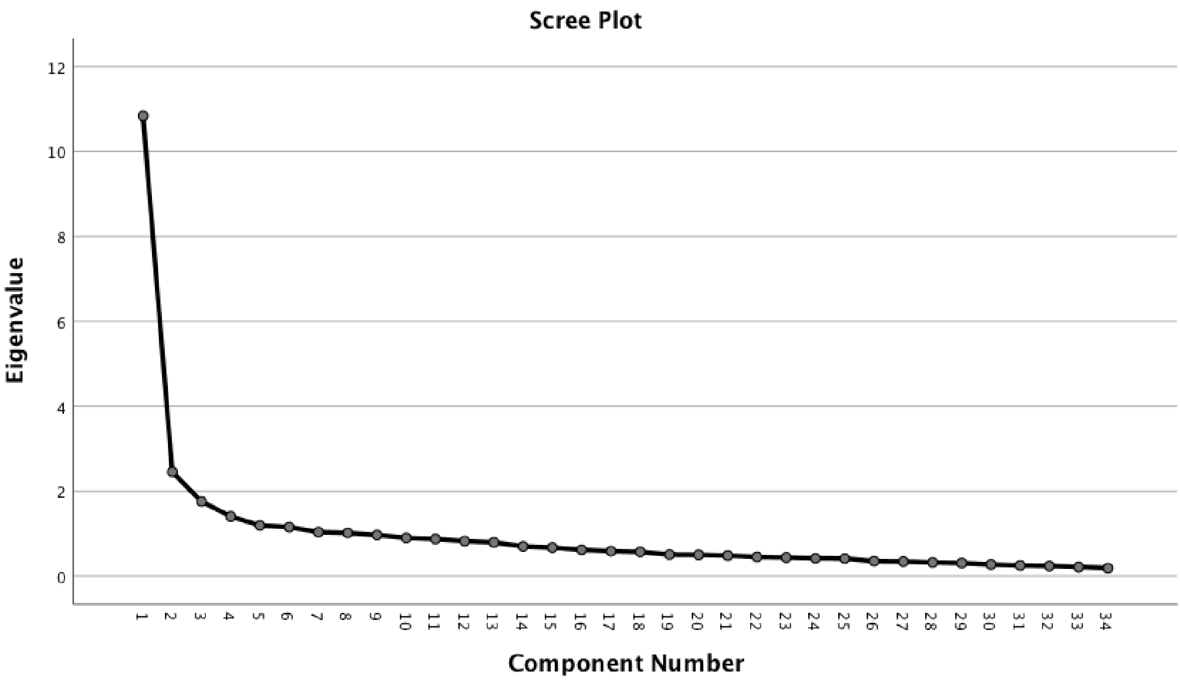


Figure 5.1 Scree Plot of the data set

After establishing the number of factors, it is important to examine the correlation between the measurement items to latent factors. This can be completed through VARIMAX rotated common factor analysis matrix and the results for this study are shown in Table 5.10 below. According to Hair, Black and Babin (2010), the loading value for each measurement item should exceed 0.50. This not achieved by one item that DT9, so it is removed from the analysis.

Rotated Factor Matrix[a]

	Factor 1	2	3	4
IE1				.708
IE2				.765
IE3				.719
IE4				.860
IE5				.724
IE6				.709
LM1	.662			
LM2	.674			
LM3	.720			
LM4	.903			
LM5	.782			
LM6	.705			
LM7	.670			
LM8	.705			
LM9	.746			
LM10	.670			
LM11	.639			
DT1		.714		
DT2		.907		
DT3		.686		
DT4		.771		
DT5		.670		
DT6		.720		
DT7		.666		
DT8		.676		
DT10		.708		
DT11		.611		
OP1			.640	
OP2			.733	
OP3			.819	
OP4			.691	
OP5			.666	
OP6			.711	

Table 5.10 Loading patterns of measurement items on constructs

In summary for EFA firstly the data set's suitability for factor analysis is examined through KMO and Bartlett's tests. This is followed by an analysis of the SPSS results from the Total Variance Explained and Scree Plot, which identified four factors that align with measurement items matching the four research constructs outlined in the theoretical framework. A further examination on loading patterns revealed that the measurement items aligned with the factors that they are intended to measure. However, in initial analysis there is one measurement items that did not pass convergent validity that is DT9. To achieve convergent validity this item was removed from the analysis. Thus, the EFA process effectively established both content and convergent validity as adequate. To fully validate the construct validity, however, discriminant validity should be examined through CFA. As the next step, analysing common method variance is necessary before advancing to CFA, ensuring a comprehensive alignment with the research theory.

5.7. Confirmatory Factor Analysis (CFA)

Evaluating the effectiveness of a measurement model within a single group is commonly done using confirmatory factor analysis (CFA), a specific method under the umbrella of SEM (Cheung and Rensvold, 2002). The overall suitability of a measurement model is assessed through confirmatory CFA. EFA and CFA are similar as they both explore the relationship between measurement items and latent factors, while CFA predefines the constructs based on theoretical framework of the study while EFA does not take account the theoretical framework while testing for construct validity (Hair, Black and Babin, 2010). At this stage, an inadequate fit signals the necessity for additional refinement of the measurement model and before the progression to SEM (Ho, 2006).

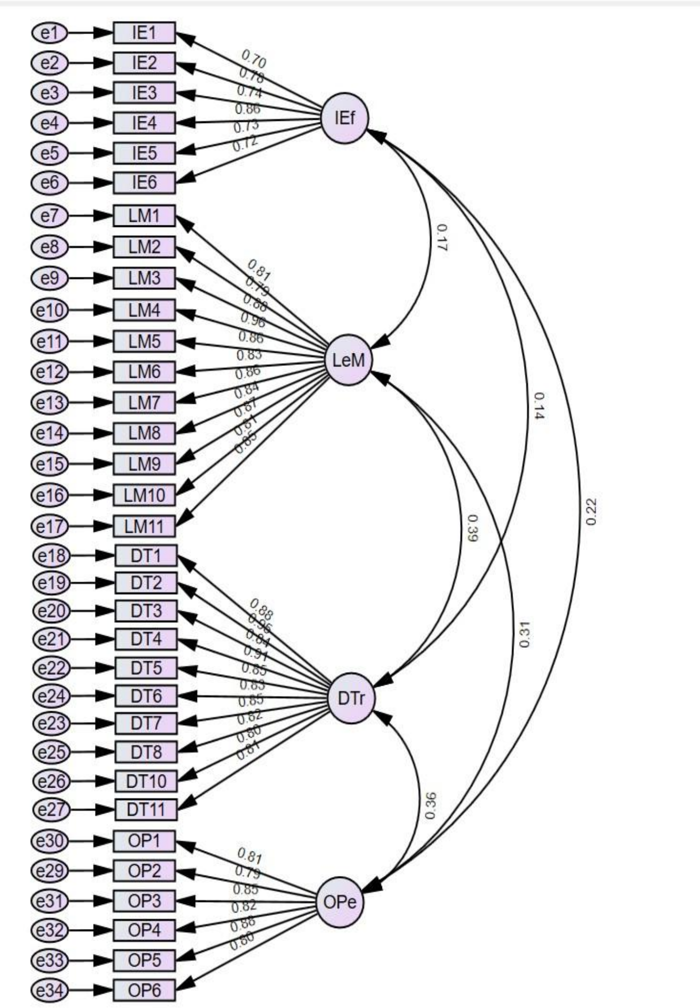
In CFA, a model is considered suitable if its proposed data relationship patterns closely resemble the real data patterns from the study, indicated by a high goodness of fit (GOF) index score (Cheung and Rensvold, 2002). In essence, GOF provides the metrics to examine how well the proposed model matches or predicts the observed covariance matrix (Ho, 2006). There is no specific answer on the GOF but according to various literature the fit index can be summarized with the description and conditions in Table 5.11 below.

	Name of index	**Description**	**Acceptable fit**
Absolute fit	Relative Chi-square (X^2/degree of freedom)	It reflects the fitness between the model and data set where lower value means better fit.	Value<5
	Root mean square error of approximation (RMSEA)	It is used to examine how well a model fits the population from which the sample is drawn. It estimates the lack of fit in a model compared to a perfect model.	Value<0.08
	Goodness of Fit Index (GFI)	It assesses the extent which the model provides a better fit in comparison to having no model	≥ 0.80

		where higher values show a better fit.	
Incremental Fit	Normed Fit Index (NFI)	NFI assesses model fit by comparing the chi-square values of the estimated model and a null model. The NFI value ranges from 0 to 1, with a value of 1 indicating a perfect model fit.	>0.90
	Non-normed Fit Index (NNFI) identical to Tucker-Lewis's index	It analyses how well the model fits the dataset.	>0.90
	Comparative Fit index (CFI)	Similar to NFI, CFI compares the fit of the model as an overall fit to data compared to the null model. Sample size is smaller.	>0.90
Parsimonious fit	Incremental Fit Index (IFI)		>0.90

Table 5.11 Fitness index according to literature adapted from (Ho, 2006; George and Mallery, 2010; Hair, Ringle and Sarstedt, 2011; Pallant, 2020)

The GOF indexes are classified into the groups that are absolute, incremental, and parsimonious fit. While there is no agreement on what fit indexes to use, it is recommended to use at least one fit index in each category (Hair, Black and Babin, 2010). The results of CFA are displayed in Figure 5.2 and Table 5.12 below, where the upcoming sections offer in depth analysis on the results.



CMIN=717.690; DF=489; CMIN/DF=1.468; p=.000; RMSEA=.048; CFI=.963; GFI=.842, IFI=.963; NFI=.894, TLI=.960

Figure 5.2 CFA results

Name of Category	Name of index	Acceptable fit	Model
Absolute Fit	**Chi-square**	≥ 0.05	717.690
	Chi-square/df	<5	1,468
	RMSEA	<0.08	0,048
	GFI	≥ 0.80	0.842
Incremental Fit	NFI	>0.90	0.894
	TLI	>0.90	0,960
	CFI	>0.90	0,963
Parsimonious fit	**IFI**	>0.90	0,963

Table 5.12 Results of measurement model in comparison to fit index

5.7.1. Validity and Reliability through CFA

Following the CFA for each item in the measurement model, the validity and reliability of every individual construct need to be established. This involves the calculation and analysis of specific metrics that are indicative of each construct's validity and reliability. As previously explained in Section 5.2 and illustrated in Table 5.2, the assessment construct validity includes assessment of both discriminant and convergent validity where the data is gathered through CFA. Further, for each construct the assessment of construct reliability is achieved through examination of internal reliability and composite reliability. Table 5.13 explains the overview of assessment of validity and reliability completed for each construct that will be explained in detail in upcoming section.

		Measures	Model
Data Validity	Discriminant Validity	Correlations between all constructs lower than 0.85	Table 5.14
	Convergent Validity	AVE ≥ 0.50	Table 5.15
Reliability	Internal Reliability	Cronbach alpha ≥ 0.70	Table 5.14
	Composite Reliability (C.R.)	C.R ≥ 0.6	Table 5.14

Table 5.13 Validity and reliability measures for model

5.7.1.1. Convergent Validity through CFA

For construct validity, convergent validity is necessary as it indicates the extent to which measurement items consistently and coherently represent the model constructs (Ruel *et al.*, 2021). Preliminary assessment of convergent validity is completed in previous section by examining factor loadings, where minimum factor loading of 0.50 need to be established. In this preliminary assessment, one item that is DT9 is removed from the model due to having a loading below 0.4. Through this process, all the remaining measurement items had factor loadings are between 0.607 and 0.907 that is higher than the threshold. To further confirm convergent validity, the conventional method is by computing the Average Variance Extracted (AVE) and Composite Reliability

(CR). For a construct to satisfactorily pass the test of convergent validity, its AVE and CR needs to be above 0.5 and 0.7, respectively.

For AVE, this threshold signifies that more than half of variance in the measurement items are accounted for their construct which indicates a strong level of shared variance (Hair, Black and Babin, 2010). The AMOS software does not have a direct computational function to provide AVE, hence the following formula is used for all constructs, where n is number of observed variables, L is the standardised factor loading:

$$\mathrm{AVE} = \frac{\sum_{i=1}^{n} L_i^2}{n}$$

Similar to AVE, another important metric that is not directly computable by AMOS is composite reliability (CR). The below formula is used to calculate where λ is the loading factor, δ is the error variance.

$$\mathrm{CR} = \frac{\left(\sum_{i=1}^{i} \lambda_i\right)^2}{\left(\sum_{i=1}^{i} \lambda_i\right) + \left(\sum_{i=1}^{i} 1 - \delta_i^2\right)}$$

For each construct AVE and CR values are calculated and is displayed in Table 5.14 showing that all of constructs have above the aimed threshold. More specifically, AVE and CR values of all constructs are above 0.5 and 0.7, respectively. This together with the factor loadings, substantiates that convergent validity is achieved. Overall, the measurement items for each construct are coherent and sufficiently represent the construct as summarised in Table 5.14.

Construct	**Crohnbach Alpha**	**CR**	**AVE**	**MSV**	**ASV**
Institutional Effects	0.887	0.884	0.561	0.050	0.033
Lean Manufacturing Principles	0.966	0.968	0.682	0.153	0.092
Digital Transformation Technologies	0.957	0.956	0.686	0.153	0.101
Operational Performance	0.927	0.912	0.634	0.130	0.092

Table 5.14 Results of CFA for constructs in the model

5.7.1.2. Discriminant Validity

Another aspect is discriminant validity, which can be assessed through the Fornell-Larcker criterion (Fornell and Larcker, 1981). As previously mentioned, discriminant validity aims to analyse how measurement items to differentiate effectively between related but distinct constructs (Ruel *et al.*, 2021). To assess this Fornell and Larcker (1981) set out a test that involed square root of the AVE of each construct and inter-correlations to be displayed on a table. In Table 5.15, the square roots of the AVEs for each construct are highlighted in bold. This table also includes the correlations between constructs, which are derived from the data obtained through CFA.

	IE	LM	DT	OP
IE	**0.314***			
LM	0.168**	**0.466***		
DT	0.145**	0.391**	**0.471***	
OP	0.224**	0.309**	0.36**	**0.402***

Note: *Square root AVE, **correlation between construct (<0.85)

Table 5.15 Correlation between constructs in the model

According to Fornell-Larcker criterion, for each construct the root square of should exceed the correlations between that construct and all other constructs in the model (Fornell and Larcker, 1981). Analysing Table 5.14, for all constructs square root of AVE is higher than their correlation to other constructs. Furthermore, Maximum Shared Variance (MSV) and Average Shared Variance (ASV) are also computated for each construct where AVE value needs to be higher than MSV and ASV to confirm discriminant validity (Hair, Black and Babin, 2010). As displayed in Table 5.14, for each construct AVE is greater than both MSV and ASV. Overall, assesing the constructs through Fornell-Lacker criterion and also conveying that AVE is greater than ASC and MSV for each construct it can be said that discriminant validity is achieved in this measurement model.

5.8. Structural Equation Modelling (SEM)

The CFA analysis showed that the measurement model had good fit indexes accompanied by convergent and discriminant validity so next SEM is utilized to test the structural model for theorised constructs. The structural model is generated to analyse the relationship between Institutional Effects (IE), Lean Manufacturing (LM) principles, Digital Transformation (DT) technologies and Operational Performance (OP) variables. The Figure 5.3 illustrates the structural model.

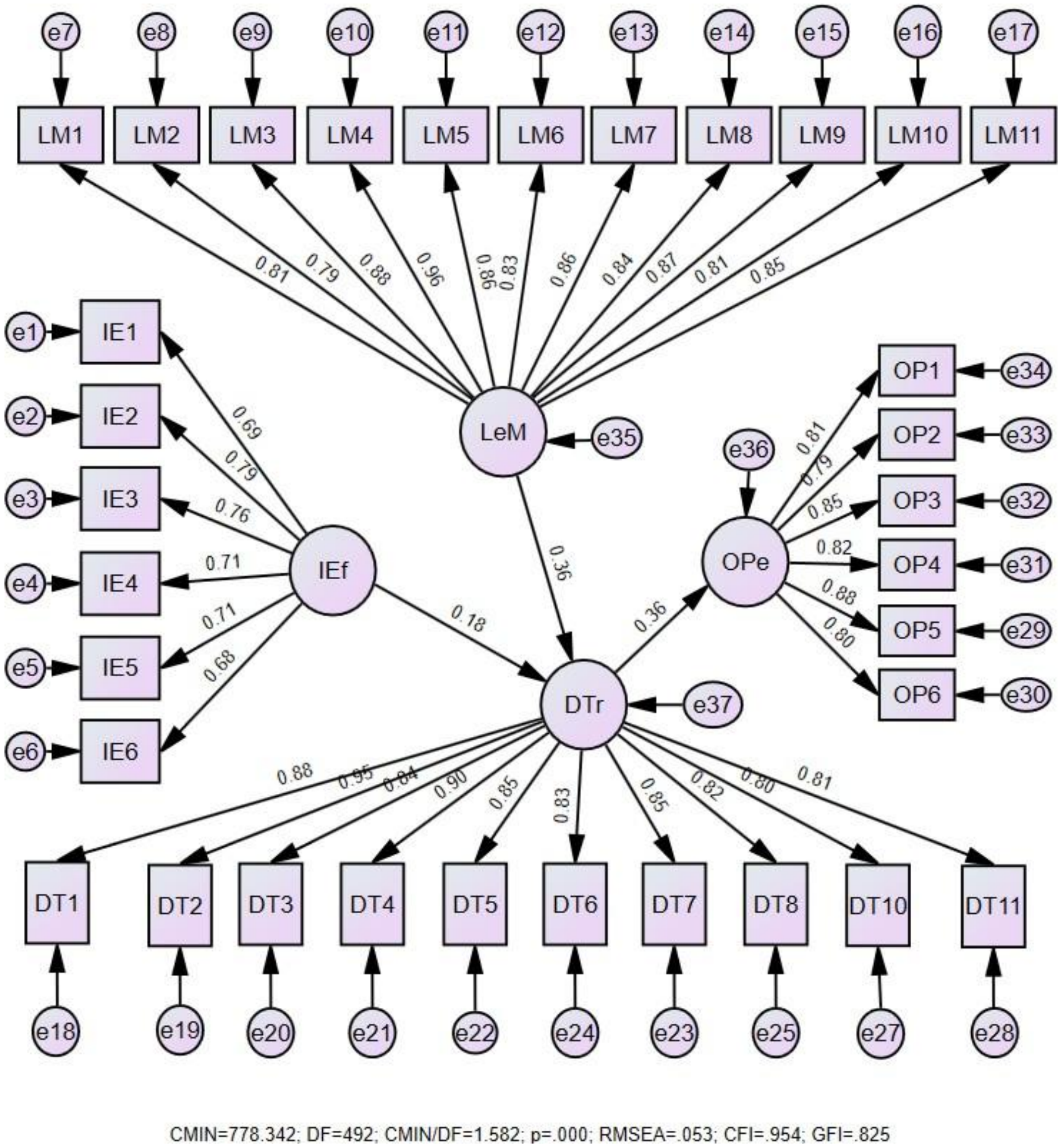


Figure 5.3 The results of SEM Model

While this structural model is generated to test the constructs, it is important to assess goodness of fit (GOF) as displayed in Table 5.16 below. Most values illustrate good fit except chi-square. Chi-square/df indicates a good fit with a value 1.48 that is lower than aimed threshold 5. The results for TLI, CFI, and IFI all achieved the recommended value with 0.960, 0.963 and 0.963 respectively, which is higher than the 0.90 criteria. Additionally, NFI is just below the desired threshold with 0.893.

GOF index	Recommended Criteria	Model
Chi-square	≥ 0.05	000
Chi-square/df	<5	1.582
RMSEA	<0.08	0.053
GFI	≥ 0.80	0.841
NFI	>0.90	0.893
TLI	>0.90	0.960
CFI	>0.90	0.954
IFI	>0.90	0.963

Table 5.16 Assessment of the model according to fit index

5.8.1. Hypothesis Testing

In previous section SEM model fit was accepted analysed through fit index. To evaluate the hypothesis testing causal effects are explained using the Table 5.17 below. The significance is assessed through p-value.

Constructs Relationship	Estimate	P	Result
IE - DT	.182	**	Significant
LM - DT	.360	***	Significant
DT - OP	.359	***	Significant

Table 5.17 Hypothesis testing for causal effect of exogenous variables on endogenous variable

Firstly, the analysis of the IE-DT results reveals a relationship estimate of 0.218, indicating a positive impact, and it is statistically significant at the 0.01 level. Meanwhile, the relationship between LM and DT technologies demonstrates a strong link, with an estimate of 0.419 that is statistically significant at the 0.001 level and a critical ratio of 5.365. Additionally, the DT technologies exhibit a positive effect on OP variables with an estimate of 0.227, low uncertainty, a critical ratio of 3.543, and significant at the 0.001 level.

5.8.1.1 Relationship between Institutional Effects and Lean Manufacturing

The analysis reveals a moderate positive influence on the adoption of Digital Transformation Technologies, as indicated by the standardized path coefficient of 0.18 ($p < 0.01$). This finding as summarised in Figure 5.4, supports the hypothesis (H1), which states, *“Institutional Pressures have a positive effect on the adoption of Digital Transformation technologies.”*

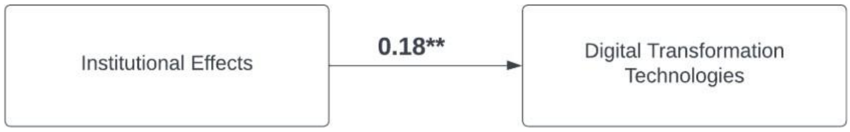


Figure 5.4 Relationship between IE and DT technologies constructs from SEM

To explore this further, Institutional Effects construct comprises three dimensions that are mimetic, coercive and normative effects, with two indicators each, totalling six variables. These six items each demonstrate an acceptable to good representation of Institutional Effects, with factor loadings ranging from 0.682 to 0.794, all exceeding the threshold of 0.60, which is generally acceptable in SEM analysis as shown in Table 5.18. The findings confirm that the items for mimetic, coercive, and normative effects accurately represent Institutional Effects. Consequently, the results provide valuable insights into the mechanisms by institutional pressures influence the adoption of Digital Transformation Technologies.

		Item Code	**Factor Loading**
Institutional Effects	Mimetic Effects	EI1	0.686
		EI2	0.794
	Coercive Effects	EI3	0.758
		EI4	0.714
	Normative Effects	EI5	0.705
		EI6	0.682

Table 5.18 Factor loadings for IE construct items

5.8.1.2. Relationship between Lean Manufacturing and Digital Transformation

The SEM analysis reveals a positive impact on the adoption of DT Technologies, as indicated by the standardized path coefficient of 0.36 ($p < 0.001$) as summarised in Figure 5.5. This supports the hypothesis (H2), which states: *“Lean Manufacturing principles have a positive effect on the adoption of Digital Transformation technologies”*

Figure 5.5 Relationship between LM and DT constructs from SEM

Focusing on each LM Principles construct, 11 items were identified as representative items for including Waste Elimination, Build-in Quality, Kanban, Standard Work, Continuous Improvement, and People & Teamwork. The factor loadings for these items, as shown in Table 5.19, are all well above the generally accepted threshold of 0.70, confirming strong correlations between the items and the construct. This indicates that the indicators reliably measure the underlying LM principles construct and highlights the positive contributions of each principle to the adoption of digital transformation.

		Item Code	Factor Loading
Lean Manufacturing Principles	Waste Elimination	LM1	0.814
		LM2	0.792
	Build-in Quality	LM3	0.876
		LM4	0.956
	JIT/Flow	LM5	0.860
		LM6	0.826
	Standard Work	LM7	0.863
	Continuous Improvement	LM8	0.836
		LM9	0.874
	People & Teamwork	LM11	0.848
		LM10	0.812

Table 5.19 Factor Loadings for LM principles

5.8.1.3. Relationship between Digital Transformation and Operational Performance

The relationship between Digital Transformation Technologies and Operational Performance is illustrated in Figure 5.6, where the results indicate a significant relationship with a path coefficient of 0.36 ($p < 0.001$). This finding provides strong support for the hypothesis (H3), which posits that *"Digital Transformation technologies have a positive effect on operational performance"* as validated by the SEM analysis.

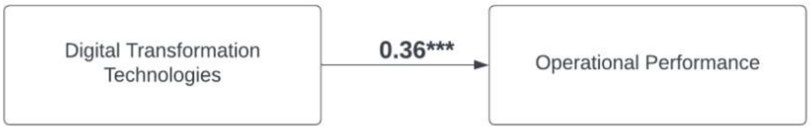


Figure 5.6 Relationship between DT and OP constructs from SEM

Digital Transformation Technologies are represented by 10 items covering Simulation & Digital Twin, Big Data, Robotics & Automation, Cloud Computing, Cyber-physical Systems, Artificial Intelligence, and Additive Manufacturing. These items are shown to have strong correlations with the DT construct, as reflected in their factor loadings summarized in Table 5.20. All factor loadings exceed the 0.8, indicating that each technology reliably measures the DT construct and effects operational performance. Further, the strong factor loadings validate the DT technologies individually and collective impact on enhancing Operational Performance and improving organizational outcomes.

		Item Code	Factor Loading
	Simulation & Digital Twin	DT1	0.881
		DT2	0.952
	Big Data	DT3	0.835
		DT4	0.903
	Robotics & Automation	DT5	0.847
		DT6	0.829
	Cloud Computing	DT7	0.845
	Cyber-physical Systems	DT8	0.816
	Artificial Intelligence	DT10	0.797
	Additive Manufacturing	DT11	0.806

Table 5.20 Factor Loadings for DT technologies

5.9. Chapter Summary

This chapter focused on analysing the data following the structured steps outlined in Chapter 4. The online questionnaire results, consisting of 208 responses, were processed during the preliminary data analysis phase. Firsly key prerequisites, including data normality, reliability, and validity, were established to ensure the robustness of the analysis. The process began with Exploratory Factor Analysis (EFA) to uncover the underlying structure of the variables and constructs without prior definition. The EFA results aligned well with the conceptual model, enabling the progression to Confirmatory Factor Analysis (CFA). In the CFA phase, the aim is to assess how closely the data aligns with the intended conceptual model. Only after successfully confirming the model through CFA was the analysis advanced to Structural Equation Modelling (SEM). SEM was used to examine the relationships among variables, employing methods such as factor loadings and fit indices. These outcomes were instrumental in testing the hypotheses formulated in Chapter 3. The analysis revealed that all hypotheses were supported, as summarized in Table 5.21, with detailed discussions of the hypothesized relationships presented in the preceding sections. The subsequent chapter will focus on interpreting these findings in the broader context of the study.

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Code	Hypothesis	Findings
H1	Institutional Effects have a positive effect on adoption of Digital Transformation technologies Lean	Supported
H2	Manufacturing Principles have a positive effect on adoption Digital Transformation technologies	Supported
H3	Digital Transformation Technologies have a positive effect on Operational Performance	Supported

Table 5.21 Research findings on hypotheses testing

Chapter 6: Discussion

6.1. Chapter Introduction

This study introduced a framework based on institutional and contingency theories to examine the relationship between Lean Manufacturing principles, Digital Transformation technologies, and the operational performance. After introducing the framework at Chapter 3, quantitative research methodology was used to validate and test the conceptual framework. The data was collected from 208 participants from manufacturing SMEs in Turkey through questionnaire survey and the data was used for SEM. The data analysis was explained in detail in the previous Chapter 5. The upcoming chapter will the discuss of these findings, building on the results presented in the preceding chapter.

6.2. Overview of empirical findings

Analysing the results of the analysis outlined in Chapter 5, the model proposed in the study demonstrates a strong structural fit, as evidenced by various fit indices such as the Chi-square ratio, RMSEA, GFI, CFI, IFI, and NFI (Chi-square ratio = 1.582, RMSEA =0.053, GFI =0.841, CFI = 0.954, IFI =0.963, NFI=0.893). Furthermore, all the hypotheses were supported. One item was removed from the aimed measurement items due to inconsistencies in the data.

Viewed through the lens of institutional theory, the conceptual framework illustrates the interconnection between LM principles, DT technologies, and operational performance, providing evidence of their collective impact on organizational outcomes. The refined framework aligns theoretical constructs with empirical evidence, as shown in the summary Figure 6.1. This supports the validity and practical relevance of the proposed relationships in the context of this study.

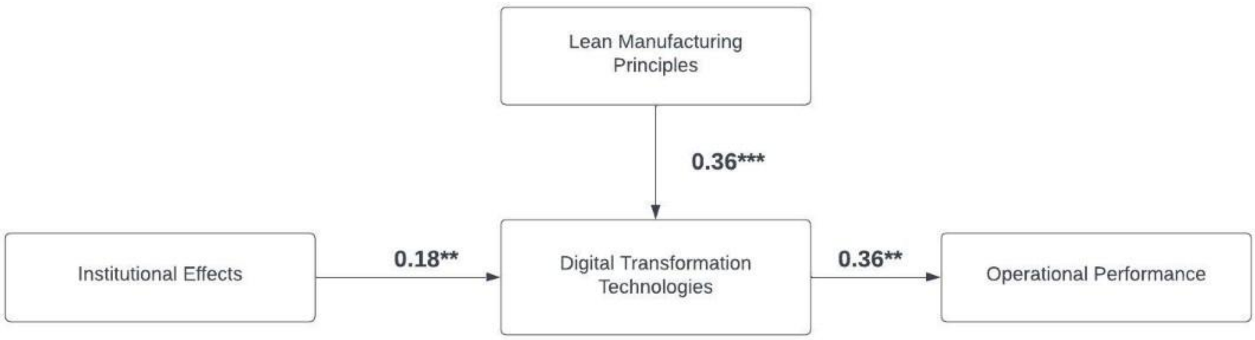

Figure 6.1 Overview of SEM results for conceptual model

Overall, the results show that both institutional effects and LM principles positively influence the adoption of DT technologies in SMEs in the Turkish manufacturing sector. LM principles has a positive influence on DT technologies with standardized coefficients of β=0.36, at a statistically significant level of 0.001. While institutional pressures also have a positive impact on DT technologies (β=0.18), they are not as statistically significant as LM principles (sig. at the 0.01 level). Moreover, the study reveals that DT technologies have a strong and statistically significant effect on operational performance, indicating that the presence of DT technologies drive improvements in operational performance criteria.

These statistical findings are complemented by prior studies that include practical implementation drawn from Turkish SMEs, showing how LM principles have been successfully combined with DT technologies to improve operational performance. For example, a case study of a Turkish SME demonstrated the use of VSM to aid simulation as a DT technology (Guner Goren, 2017), which aligns with broader studies that identifies VSM and simulation as among the most commonly applied tools for integrating LM and DT (Yilmaz *et al.*, 2022). In comparing these results with prior studies, the positive and significant influence of LM principles on DT adoption aligns with international findings (Buer, Strandhagen, *et al.*, 2020; Sony *et al.*, 2022) . However, existing literature shows no clear consensus on the impact of institutional pressures in DT (Lin and Sheu, 2012; Krell, Matook and Rohde, 2016), which will be discussed in detail in relevant sections.

Building on these empirical results, the sample had a variety of large sectors and process types that are job shop, continuous and batch production. The sample shown in Table 5.2 represents a diverse range of sectors, with the largest shares coming from machinery, automotive and aerospace (18.3%), metal and metalworking (17.8%), and textiles (16.8%). Production types were distributed across batch (53%), continuous flow (47.6%), and job shop (23.2%) environments. Production types tend to align with specific sectors: batch production is more common in metalworking, wood, paper, and plastics; continuous flow predominates in high-volume, repetitive-cost industries such as automotive and pharmaceuticals; and job shop operations are typically found in woodworking, specialized machinery manufacturing, and custom metal fabrication (Fransoo and Rutten, 1994; Luhn *et al.*, 1999; Dennis and Meredith, 2000; Panwar, Jain and Rathore, 2015).

This distribution is relevant because the production environment influences how DT technologies are applied together with LM principles. For example, continuous flow principle may more readily integrate automation such as in metal parts manufacturing (Luhn *et al.*, 1999; Singh, 2018), while job shop contexts may emphasise flexible manufacturing systems and digital scheduling tools to address complexity and variability as addressed in the case study by (Choi, Hwang and Kim, 2023)). Understanding how sector and production type are connected enables better interpretation of the results and helps tailor DT strategies for each industry, which will be illustrated further in this section with relevant sector-specific and production-type examples.

These findings fill a research gap regarding the empirically validating the conceptual model and positive impact of LM principles and DT technologies from an institutional theory perspective and offer insights into the adoption of DT technologies in Turkish manufacturing SMEs. The following section will provide a comprehensive examination of the hypotheses in the context of these findings. It will explore how the results align with the literature review, highlighting key theoretical contributions and practical implications for the Turkish manufacturing sector.

6.3. Impact of Institutional Effects on Digital Transformation

Hypothesis H1 suggested that institutional effects positively influence DT technologies, categorized into mimetic, coercive, and normative types. The statistical analysis confirmed H1 with a significant path coefficient (β=0.18) to DT at a p-value of ≤ 0.001. All items demonstrated strong correlations with the institutional effects construct, with mimetic, coercive, and normative effect items displaying positive factor loadings above 0.7. This, along with the positive path coefficient from institutional effects to digital transformation, indicates that mimetic, coercive, and normative pressures collectively exert a positive influence on digital transformation efforts. These findings highlight the role of external institutional pressures in driving digital transformation efforts, suggesting that SMEs in the Turkish manufacturing sector respond to external demands not only to remain competitive but also to comply with industry expectations and norms.

Focusing on the existing literature, there is no clear consensus on the impact of individual institutional pressures in the context of DT and innovation. Some studies align with the empirical findings of this research, highlighting positive institutional effects across different regions, including developing countries. For example, Krell, Matook and Rohde (2016) found that institutional pressures positively influence the adoption of DT technologies such as ERP systems. Their study revealed that different external pressures affect various aspects of the adoption process: normative and coercive pressures were shown to enhance project management approaches, while mimetic pressures positively impacted team competence through the imitation of best practices and knowledge transfer. Conversely, other studies suggest that coercive and normative pressures may have neutral or even negative effects on DT adoption (Lin and Sheu, 2012; Zhu, 2016; Beta and Ogunmokun, 2023). These contrasting findings highlight the complexity and context-dependent nature of institutional pressures, making the results of this study interesting. Hence, this research will analyse each institutional pressure individually to better understand their roles in driving DT adoption.

Effectively analysing institutional effects requires careful examination of their sources of pressure, which primarily originate from competitors, government, industrial bodies, and customers, as detailed in Table 3.3 (Section 3.3.1). Examining these pressure sources and their impacts within each country's specific context is crucial, with coercive and normative effects particularly influenced by varying legal frameworks and cultural norms, resulting in diverse compliance requirements and societal norms (Krell, Matook and Rohde, 2016; Jiao, Yang and Cui, 2022). A notable example of this variability is the extent of government support for SMEs, which differs widely between countries. Some nations prioritize SMEs by implementing specialized programs, training initiatives, and sector-specific support centres aimed at fostering growth and innovation within the manufacturing sector (Sevinç and Eren, 2019; van Dam *et al.*, 2021). These country-specific initiatives can significantly impact the adoption of DT technologies and operational performance improvements in SMEs, highlighting the importance of adapting institutional analyses to the local context. Therefore, to conduct a meaningful analysis of institutional effects, it is crucial to focus on the contextual and country-specific factors that shape these pressures. By tailoring the examination, the mechanisms driving institutional effects and their implications for DT technology adoption can be understood in diverse settings.

In following section, each institutional effect component is analysed in the context of Turkey, focusing on pressure sources and external influences relevant to SMEs. This analysis aims to provide insights into the findings obtained in the previous section and explain the depths of institutional effects influence on the adoption of DT technologies within SMEs.

6.3.1. Impact of Mimetic Pressures on Digital Transformation

The empirical results revealed that mimetic pressures, with factor loadings of 0.68 (IE1) and 0.79 (IE2) emerged as a key contributor to institutional effects, which in turn positively influenced DT technologies with a path coefficient of $\beta = 0.18$ ($p \leq 0.001$). This highlight the influence of competition driving DT technology adoption, where SMEs are compelled to align with industry trends and successful practices established by their competitors (Omrani *et al.*, 2022). Analysing the Turkish manufacturing ecosystem reveals two key causes of competition and mimetic pressures: leading benchmarks set by large enterprises on DT technologies and a widespread display and support for its adoption.

Firstly, mimetic pressure intensifies when competitors gain competitive advantages by adopting DT technologies, compelling other companies to benchmark against these successful adopters, as noted by (Huang *et al.*, 2023). In Turkey, this dynamic is particularly evident in sectors with prominent manufacturers that establish industry benchmarks and heighten competition for SMEs. For example, the Turkish automotive sector hosts global giants such as Mercedes-Benz, Renault, Ford, and Isuzu, all of which have manufacturing plants in Turkey that produce a variety of vehicles, creating a competitive benchmark for SMEs (Masaci, 2024). One notable example of such benchmarking is the Brisa factory in İzmit, Turkey, a joint venture partially owned by Bridgestone. This cutting-edge smart factory incorporates advanced DT technologies, including robotics, automation, and big data analytics, achieving an impressive production rate of one tire every 2.5 seconds (Vardar, 2020; Brisa, 2024). SMEs working closely with Original Equipment Manufacturers (OEMs) like Brisa can observe, learn, and adopt these transformative technologies. Moreover, Brisa actively contributes to the ecosystem by initiating educational programs to train their suppliers and dealers on DT adoption (Gülşen T., 2021). Similarly, in another industry example Şişecam, Europe and Turkey's largest manufacturer in the glass industry, has set a benchmark for DT adoption by integrating technologies such as automation, collaborative robots, and digital supply chain tracking in Turkey (Şişecam, 2024). Şişecam has closely involved its suppliers in adapting to these advancements, further propagating DT adoption within its network (Şişecam, 2022). These examples illustrate how leading manufacturers of the world are present in Turkey within the industry are source of mimetic pressures, fostering widespread DT adoption among SMEs and enhancing industrywide competitiveness.

Secondly, companies tend to focus on their competitors' achievements as a reliable option and when faced with an uncertainty or a risk such as digital transformation and as a result mimic others that succeeded (Jiao, Yang and Cui, 2022). Hence, high display and advocation of these results among manufacturers create a sense of temptation and competition in SMEs. For example, achievements like those of companies Brisa or Şişecam through DT technologies such as robotics and automation tempt SMEs competing in the same industry to emulate these practices (Vardar, 2020). Leading manufacturers in Turkey frequently hold meetings to demonstrate the benefits and practical applications of DT technologies to their suppliers, most of which are SMEs, where a notable example is Ford Otosan. The company launched the "Plant of the Future" initiative to modernize the Turkish manufacturing ecosystem with sustainable, digital, and efficient solutions, which aims to foster growth in the automotive ecosystem and among suppliers through future-oriented investments (Otosan, 2023). Similarly, the white goods manufacturer Arçelik utilizes an online training portal and conducts meetings to promote the adoption of digital transformation among its stakeholders (Arçelik, 2022). Likewise, TOFAŞ employs a DT maturity index to support its SME suppliers by offering financial aid and resources to those with higher maturity levels, thereby enhancing their competitive positioning (TOFAS, 2022). These initiatives to demonstrate, promote, and emphasize the advantages of DT technologies generate strong mimetic pressures within the Turkish manufacturing ecosystem, fostering the widespread adoption of digital transformation technologies among SMEs.

Overall, the empirical results have shown that mimetic pressures are a key component of institutional pressures, which positively influence the adoption of DT technologies in Turkish SMEs. This is further reinforced by the current Turkish ecosystem, as this section has provided numerous examples of large manufacturers setting industry benchmarks, serving as significant drivers of mimetic pressures. The widespread implementation of DT technologies by these leading enterprises provides SMEs with clear models to emulate, fostering competitive dynamics within the industry and accelerating the adoption of DT technologies across the sector. Hence, it can be said that the empirical results are supported by the practical realities and examples observed within the Turkish manufacturing landscape.

6.3.2. Impact of Coercive Pressures on Digital Transformation

The research findings indicate that coercive pressures exerted by the Turkish government promote DT adoption in SMEs, as evidenced by factor loadings of 0.758 and 0.714 to institutional pressures, which, in turn, demonstrate a positive path coefficient of 0.22. This finding is particularly intriguing, given the limited literature addressing the effects of the Turkish government's encouragement for SMEs in this context, alongside empirical research from other developing countries that has shown contrasting results where for instance, in Africa, government pressures were perceived as overly demanding that caused coercive pressure to be negative (Beta and Ogunmokun, 2023). Coercive pressures typically stem from government interventions through regulations, laws, and policies (Fogaça, Grijalvo and Neto, 2022). Therefore, it is crucial to examine the Turkish government's role in fostering DT adoption among SMEs. A detailed introduction of this topic is provided in Chapter 2, Section 2.3.4 of the literature review, which explores DT adoption in Turkey and is further summarized and analysed below.

In Turkey, the government plays a pivotal role in supporting SMEs through a variety of strategies through its agency called KOSGEB. As a short summary, since 1990, KOSGEB as the government institution supporting SMEs, offers providing services including financial assistance, training programmes and consultancy services (Sevinç and Eren, 2019). SMEs are tempted to adopt DT technologies as KOSGEB provides financial assistance, including non-repayable and repayable funds, and facilitating bank credits for SMEs investing in digital transformation technologies, with support reaching up to 20 million TL (approximately 500 thousand euros) for each qualifying SME (KOSGEB, 2024a). Due to this financial support, want to invest in DT technologies, which normally viewed as risky and expensive for SMEs that have financially limited (Ghobakhloo and Fathi, 2020).

In terms of other sources of coercive pressures, Turkish government together with United Nations Development has an initiative called 'model factories' for manufacturing SMEs that provides training and consultancy services for digital transformation and lean manufacturing (Turkish Ministry of Industry and Technology, 2023b). Designed to facilitate the adoption of digital technologies and improve the digital literacy of their workforce, these factories are strategically located near key manufacturing areas and case studies show that they can increase productivity up to 76% and throughput by 140% (Duyar, 2024). These case studies on Model factory do not only source of coercive pressure also support mimetic pressures as SMEs tend to follow the good practices among the competitors (Jiao, Yang and Cui, 2022). Turkish government also provided accessibility to SMEs in different locations so they can be part of Model factories and DT trainings as currently there are 8 model factories in Turkey situated close to industrial sites with 4 more factories underway (Albayrak, 2023). Through these initiatives, Turkish government creates a coercive pressure, where establishing DT that allow training centres but also financial support, creating accessibility amongst SMEs so that they want to adopt DT technologies.

Regarding digital transformation in the Turkish manufacturing industry, the Turkish Informatics Industry Association (TÜSİBAD) reported in 2022 that the digital transformation index of the ecosystem showed a steady increase from 2019 to 2021, followed by a slight decrease in 2022, particularly in the aspects of legislation and taxes (TÜBİSAD, 2023). The slight decrease of 2.8% in the digital transformation index regarding legislation, taxes, and access to technology in 2022, reported by TÜSİBAD, may suggest a potential need for the Turkish government to enhance support, particularly in terms of tax incentives for SMEs. However, the consistent increase in ecosystem including politics aspect in the index until 2021 could indicates ongoing support influenced by coercive pressures.

Turkey has made notable progress to allow SMEs to adopt DT technologies, and practices from other countries could be compared and adapted. As another developing country, Brazil has a programme called Camara 4.0, which contains strategies to align public and private efforts (United Nations Conference on Trade and Development, 2022) and could be analysed for potential adoption in Turkey to unify objectives. In another comparison, Malaysia has a Digitalisation Grant Scheme under its Shared Prosperity Vision, aimed at increasing SME involvement in digitalisation to generate tangible value (Ministry of Economic Affairs, Malaysia, 2019; Yeo and Ong, 2024) . Similar to Turkey, Poland offers a Digital Maturity Assessment Tool to identify resource needs and provide evidence for funding applications tied to measurable productivity improvements (Interreg EU, 2021). Adopting similar assessment-linked funding mechanisms, could enhance the effectiveness of Turkish programmes by encouraging compliance and accelerating adoption. For advance the coercive pressure, tax incentives can be introduced to the companies that dedicate resources and invest on DT technologies as it is happening in Italy (Cugno, Castagnoli and Büchi, 2021). Together, these approaches could create a structured, incentive-driven framework that supports SMEs while compelling faster, more widespread adoption of DT technologies in Turkey.

Overall, an analysis of the Turkish government's focus on SMEs through initiatives, funding, training programs, and the establishment of Model Factories demonstrates strong support and advocacy for DT adoption in SMEs.

This aligns with the findings, confirming that coercive pressures exerted by the Turkish government positively impact the adoption of digital transformation technologies.

6.3.3. Impact of Normative Pressures on Digital Transformation

An interesting finding came from normative pressures, where normative pressure is highlighted as a driver of DT technologies in Turkish SMEs with a factor loading of 0.705 and 0.682 to institutional effects construct. This suggests that industry stakeholders, including customers and industrial partners such as suppliers, influence SMEs to adopt DT technologies as they conform to norms established by established entities (DiMaggio and Powell, 1983; Čater *et al.*, 2021). Regarding normative pressures there has been mixed results from previous studies. In manufacturing firms when it comes to involving technology, innovation, and sustainability, in some studies normative pressures played either no part is negative impact throughout various studies (Lin and Sheu, 2012; Zhu, 2016; Čater *et al.*, 2021; Kuo, Chen and Yang, 2022). For instance, a recent study has shown that there is a negative relationship between normative pressures and digital transformation in maritime industry (Kuo, Chen and Yang, 2022). A further study by Čater *et al.* (2021) analysed 124 manufacturing firms and found that adoption of Industry 4.0 technologies is not influenced by normative pressures from customers from customers or suppliers. Thus, these contrasting empirical results highlight the need for further analysis to contextualize and better understand the role of normative pressures in shaping DT adoption in Turkish SMEs.

To explain the results, it is important to note that the literature emphasizes the need to analyse normative pressures within a country-specific context, as the dynamics of industries and their participants vary significantly across regions (Martínez-Ferrero and García-Sánchez, 2017). Hence, normative pressures need to be examined in Turkey and SME specific context to draw more insight to the results. Manufacturing SMEs in Turkey are required to adhere to industry norms upheld by their suppliers and customers, such as compliance with supplier codes of conduct enforced by OEMs (Şişecam, 2024). These norms, created by both customers and suppliers, often relate to traceability, flexibility, and visualisation, driving DT technology adoption across the sector, including SMEs (Petroni and Bevilacqua, 2002; Srivastava *et al.*, 2021) and to conform these norms, Turkish manufacturers have been actively adopting DT technologies (Cebeci, 2014; Erol *et al.*, 2021).

One of the most significant norms, particularly driven by customer requirements, concerns traceability and safety in sectors ranging from food to automotive and aerospace (Liao, Kwaramba and Kros, 2020; Pop, Titu and Pop, 2023). These norms enable companies to effectively trace the source of product issues, addressing challenges like recalls and supply chain disruptions more efficiently (Dai *et al.*, 2021). For example, in aerospace industry, to comply with airworthiness standards, data on aircraft maintenance and parts need to be recorded (Ho *et al.*, 2021). For instance, Airbus utilizes technologies such as IoT in all its aircraft to enable traceability, with the adoption process beginning in 2009 (Schuitemaker and Xu, 2020). The company mandates that its suppliers, including those from Turkey, implement DT technology for traceability, with plans to procure $5 billion worth of parts and services from Turkish suppliers over the next decade (Santonino, Koursaris and Williams, 2018; Airbus, 2023). Consequently, SMEs in these industries are using technologies such as cloud, blockchain or a similar sort of technology to track parts and store information (Ho *et al.*, 2021). In automotive, food, and pharmaceutical industries, case studies in Turkey have explored the adoption of DT technologies to improve compliance with regulatory traceability requirements (Erol *et al.*, 2021). More specifically, in the food sector, technologies such as IoT, RFID, and ERP have been adopted, and for example, Turkey has implemented traceability technologies in its poultry feed for over a decade in accordance with EU regulations (Cebeci, 2014, p. 201; Keleş and Ova, 2020). Therefore, industry norms and supplier requirements on traceability in sectors such as food, automotive, and aerospace create normative pressures for SMEs to adopt DT technologies, which represent 31.8% of survey participants as outlined in Table 5.2 and 38.4% of Turkish SMEs as shown in Table 5.3.

Another source of normative pressure stems from customer expectations for manufacturing flexibility, particularly in Turkey, which is recognised for its ability to offer diverse and adaptable production capabilities (Akguner, 2024). Flexible manufacturing is closely linked with DT technologies such as additive manufacturing, which have emerged as essential components of flexible manufacturing processes as outlined in Chapter 2 (Tondini *et al.*, 2021; Javaid, Haleem, Singh and Suman, 2022). Furthermore, customers demand rapid prototyping and custom production, where prototypes shown to increases the success of new product introductions to the market (Tih *et al.*, 2016; Pallant, Sands and Karpen, 2020). To meet this demand, SMEs need to adopt new technologies and increase their capability (Petroni and Bevilacqua, 2002; Mishra, 2016) . In Turkey's flexible manufacturing scene, digital transformation technologies like automation and cyber-physical systems are being integrated into smart factory concepts to allow flexible manufacturing (Kovalenko *et al.*, 2022). Moreover, Turkish firms have embraced flexibility through the adoption of additive printing, as demonstrated in a survey of 226 manufacturing firms, highlighting its role in prototyping, enhancing competitiveness, and facilitating new product development (Turkcan, Imamoglu and Ince, 2022). Studies indicate that SMEs utilize additive manufacturing across sectors ranging from metal processing and textiles to aerospace (Ozdemir and Kagnicioglu, 2017; Top *et al.*, 2023). Therefore, customer expectations for flexible production in Turkey create normative pressures that drive the adoption of DT technologies like additive manufacturing.

A further source of normative pressure involves the digital visualization expectations from customers, with companies increasingly required by customers, including OEMs, to utilize 3D visuals as part of their toolkit. In manufacturing, suppliers are required to use specific software like Teamcenter, Solidworks, and Autocad for collaborative design processes, often to align with OEMs' adoption of Digital Twin (Niemann and Pisla, 2021; Stjepandić, Sommer and Stobrawa, 2022). The normative pressure regarding visualization is notably significant in Turkey, leading SMEs to get support from the government adopt Digital Twins, as highlighted by case studies. For instance, SMEs receive financial support from government for software purchases and training, which lead to business growth as demonstrated in the case of an aerospace parts manufacturing SME (KOSGEB, 2022). Similarly, in another Turkish SME specializing in CNC machines for dental products, KOSGEB supports the integration of visualization software to meet customer-driven demands for Digital Twin technology (KOSGEB, 2023a).

Overall, although there have been mixed results regarding normative pressures in other countries (Lin and Sheu, 2012; Zhu, 2016; Kuo, Chen and Yang, 2022), upon a closer look into the industry norms and standards set by players in the manufacturing industry in Turkey, the normative pressures are in line with results. More specifically, the pressures that Turkish SMEs receive to conform with industry where traceability is important, visualisation and flexibility is expected by customer (Petroni and Bevilacqua, 2002; Srivastava *et al.*, 2021). Consequently, Turkish manufacturers, including SMEs, are increasingly adopting DT technologies such as IoT, Digital Twin, and additive manufacturing (Cebeci, 2014; Erol *et al.*, 2021). Hence, this in-depth analysis of the Turkish manufacturing ecosystem supports the empirical results.

6.4. Impact of Lean Manufacturing on Digital Transformation

The overall analysis indicates a strong positive relationship between LM principles and DT technologies, with a β coefficient of 0.36 at the 0.001 significance level. This finding supports Hypothesis H2, suggesting that LM principles help the adoption of DT technologies. The 11 items used to measure LM principles demonstrated strong correlations with the LM construct, with factor loadings ranging from 0.792 to 0.956, indicating that all

LM principles contribute positively to the adoption of DT technologies in Turkish SMEs, as will be elaborated in the following sections.

The existing literature supports Hypothesis H2, with numerous studies conducted over the years repeatedly demonstrating a positive connection between LM principles and the adoption of DT technologies (Bortolotti, Romano and Nicoletti, 2010; Rossini *et al.*, 2023). In the Turkish manufacturing landscape, the integration of LM principles to support DT technologies has recently gained popularity, with evidence for Hypothesis H3 highlighted in recent case studies. Notably, a longitudinal study by Gürsoy (2020) examined a Turkish manufacturer that initially implemented LM principles such as waste reduction, continuous improvement, and just-in-time (JIT) practices. Following this, the firm adopted DT technologies including Kanban, IoT, and robotics. The study revealed that LM principles played a critical role in overcoming challenges associated with DT adoption, emphasizing that without these principles, the digital transformation process in the case study would have likely failed. In another recent study, focused on the DT Şimşek Demirbağ and Yıldırım (2022) adoption processes of three Turkish manufacturers that had been applying LM principles for at least two years. Their research highlighted that LM principles serve as a prerequisite for DT adoption and significantly improve the success rate of implementation. Consequently, these recent case studies among Turkish manufacturers support the assertion that LM principles not only facilitate the adoption of DT technologies but are also critical for successful implementation (Iris and Cebeci, 2014; Gürsoy, 2020; Demirbag and Yildirim, 2022).

For LM principle to have a positive influence on DT technologies, the companies in Turkey need to have a good LM awareness which is sometimes even a problem for developed countries like Qatar where LM awareness is documented to be low (Salem *et al.*, 2016). Longitudinal studies in Turkey on the maturity of LM principles provide evidence that these principles have been consistently applied and their applications have evolved over time (Satoglu and Durmusoglu, 2003; Iris and Cebeci, 2014). Consequently, it can be suggested that awareness of LM principles can support the adoption of DT technologies as displayed in case studies (Demirbag and Yildirim, 2022). However, there has been no completed quantitative study among Turkish manufacturers that specifically investigates the relationship between LM principles and DT technologies. Therefore, this study contributes to the literature by providing empirical evidence that supports qualitative research in this area.

Overall, the empirical results and analysis indicated that LM principles facilitate the adoption of DT technologies, supported by literature and case studies not only globally but particularly within the Turkish context (Bortolotti and Romano, 2012; Gürsoy, 2020; Demirbag and Yildirim, 2022). Turkish SMEs have demonstrated a strong grasp and awareness of LM principles, which form the basis and pre-requisite of this support (Satoglu and Durmusoglu, 2003; Iris and Cebeci, 2014). Moreover, each LM principle has been shown to contribute to the adoption of DT technologies according to the SEM results, and these findings will be further explored in the upcoming sections within the context of Turkish SMEs.

6.4.1. Waste Elimination and Digital Transformation

The study demonstrated that in Turkish SMEs, waste elimination has a positive impact on the adoption of DT technologies, with factor loadings to the LM construct being 0.814 (LM1) and 0.794 (LM2). This finding aligns with existing research, which identifies waste elimination as one of the most widely applied LM principles in conjunction with DT technologies in manufacturing case studies. The literature review done part of this PhD indicates that approximately 70% of companies integrating LM principles with DT technologies have utilized waste elimination as part of their adoption process (Yilmaz *et al.*, 2022). The main reason for this popularity is the understanding that eliminating waste before adopting DT technologies is crucial, as digitizing processes with waste can lead to less effective results and higher chances of failure, supported by prominent academics in the field (Bortolotti and Romano, 2012; Powell, Morgan and Howe, 2021).

Value Stream Mapping (VSM), a key tool for waste elimination as represented by LM2 item, is frequently paired with Digital Twin and simulation technologies to visualize necessary changes in materials, equipment, processes, and information flows for adopting DT technologies (Ferreira *et al.*, 2022; Yilmaz *et al.*, 2022). In line with this, integration of VSM with simulation is frequently used in Turkish SMEs in various manufacturing sectors. For instance, a sugar manufacturer in Turkey utilized simulation with VSM to visualize changes in the packaging process, leading to enhanced productivity (Emir and Gergin, 2021). A furniture manufacturing SME employed simulation to target improvements and waste reduction through VSM, resulting in reduced lead times(Guner Goren, 2017). Another case study in the automotive sector simulated current and future production processes to enhance operational performance (Aksar *et al.*, 2022). These examples highlight the popularity and effectiveness of integrating VSM and simulation in supporting DT adoption within Turkish SMEs.

Waste elimination is not only integrated with simulation but also with other DT technologies, as evidenced by several studies linking VSM with technologies like IoT, robotics and automation (Abideen and Mohamad, 2020; Balaji *et al.*, 2020; Valamede *et al.*, 2020). The rationale behind using waste elimination is that companies, especially SMEs, employ it prior to embarking on DT as waste elimination and VSM has been recognized as a crucial preparatory step before adopting DT technologies (Powell, Morgan and Howe, 2021; Demirbag and Yildirim, 2022). For instance, in the case of a Turkish SME manufacturing automotive parts, VSM was utilized to incorporate robotics into the production line following waste elimination (Yurtseven *et al.*, 2024). Similarly, another study applied VSM to facilitate the adoption of automation in a conveyor system at a tractor manufacturer in Turkey (Adalı *et al.*, 2017). Hence, as evidenced by the case studies and supporting literature waste elimination is actively used with various DT technologies such as IoT, robotics, and automation to aid the adoption process.

Overall, the literature focusing on Turkish manufacturing SMEs shows the critical role of waste elimination, aligned with empirical results, facilitated by VSM, and integrated with simulation and other DT technologies. The waste elimination principal aids in visualizing and optimizing processes for adopting DT technologies while also reducing the risks of failure, as evidenced in various case studies(Adalı *et al.*, 2017; Aksar *et al.*, 2022; Yurtseven *et al.*, 2024).

6.4.2. Built-in Quality and Digital Transformation

The strong correlation observed with the built-in quality principle is demonstrated by the factor loadings of 0.876 (LM3) and 0.956 (LM4) within the LM construct. This indicates that the built-in quality principle plays a crucial role within the LM framework, which, in turn, facilitates the adoption of DT technologies among Turkish SMEs. In this context, built-in quality serves as a foundation for the adoption of DT technologies by enabling the integration of quality control, improvement, and visualization tools with digital and vision processing techniques, thereby synergistically enhancing productivity, and improving product quality, as represented by LM3 (Viet Que *et al.*, 2023). Additionally, it aims to achieve optimal product quality, with tools such as fishbone diagrams, represented by LM4, playing a critical role in identifying root causes of issues and formulating solutions during product design and improvement processes, as discussed in Section 2.2.4 (Bicheno and Holweg, 2016; Lanati, 2018).

In Turkey, the adoption of the built-in quality principle is evident in effectively addressing problems using fishbone diagrams during the adoption of DT technologies, including simulation and big data analytics (Bakdaal and Tekez, 2021; Çakır *et al.*, 2024). In terms of simulation, problems identified through data were addressed using fishbone diagram analyses (Vo *et al.*, 2020). For example, in a Turkish SME producing lock systems, simulation is aided with fishbone diagrams to decrease the defects and reprocessing of the products (Bakdaal and Tekez, 2021). Further, in a Turkish furniture manufacturer, built-in quality principle has been used together with data simulation to improve product quality (Ersoz, Ersoz and Peker, 2018). Moreover, collected data from operators can be analysed using fishbone diagrams to identify the best operating conditions (Ly Duc *et al.*, 2023). For instance, in a case study of a Turkish company, big data analytics was integrated with defect measurement (Atagoren and Chouseinoglou, 2014). Similarly, its uses go beyond manufacturing factories to further supply chain where in Turkey fishbone diagrams are to tackle problems of data when it comes to safety (Öztürk, Mevsim and Kınık, 2019; Yücer and Ayhan, 2020). Overall, the adoption of the built-in quality principle is evidenced by the widespread use of fishbone diagrams in conjunction with DT technologies facilitating effective problem-solving and quality improvement across manufacturing and supply chain sectors.

Another advantage of built-in quality involves establishes a foundational structure that paves the way for the adoption of DT technologies, where visualisation and addressing quality issues is later enhanced through integrating with DT technologies like IoT and Digital Twin (Berk and Toy, 2009; Torres, Pimentel and Duarte, 2020). In an example, a system has been developed for Turkish automotive manufacturers, including SMEs, that integrates existing built-in quality principles with multiple DT technologies (Bayrak *et al.*, 2022). The built-in quality principle of visualizing and addressing quality issues on the shop floor is enhanced by utilizing processing technology and AI to analyse production part defects, thereby simplifying the quality control process, and displaying the data directly on the shop floor. Further, in another Turkish manufacturer, an IoT system was integrated with an ERP system to oversee production and quality control processes supported by built-in quality principles, ensuring products were promptly accepted or rejected based on predefined quality standards (Çakır *et al.*, 2024). This setup facilitated the real-time tracking and display of KPIs, including Overall Equipment Effectiveness (OEE), highlighting both quality and operational performance metrics in shopfloor. Hence, built-in quality principles laid the foundation for DT adoption, which later supported by advanced technologies like IoT and Digital Twin, to enhance the Turkish manufacturing ecosystem by enabling real-time quality control monitoring and efficient analysis of production defects directly on the shop floor.

In conclusion, the analysis of the Turkish manufacturing ecosystem highlights the significant role of the built-in quality principle in facilitating digital transformation (DT) adoption. Built-in quality plays a vital role in addressing DT adoption challenges faced by Turkish manufacturers (Atagoren and Chouseinoglou, 2014;

Bakdaal and Tekez, 2021). Furthermore, it establishes a solid foundation for DT technology integration by enabling real-time quality control monitoring and efficient analysis of production defects directly on the shop floor. This is achieved through the active integration of quality control and visualization systems with DT technologies, such as IoT (Bayrak *et al.*, 2022; Çakır *et al.*, 2024).

6.4.3. Flow and Digital Transformation

The JIT/Flow principle has been shown to support the adoption of DT technologies, as evidenced by its strong correlation with the LM construct, with factor loadings of 0.860 (LM5) and 0.826 (LM6) for the items representing JIT. To support these results, Numerous studies have highlighted the role of the JIT principle in streamlining processes for DT technologies, particularly in Turkey, since the 1990s (Aytug and Dag, 1999; Gürsoy *et al.*, 2021).Turkish manufacturers have been applying JIT principles for over three decades, with Kanban emerging as a crucial tool widely adopted in their operations (İşler, 2000). Specifically, Kanban, which signals the need for more products from one process to the next, has been extensively integrated with DT technologies. Its most prominent application, e-Kanban, provides Turkish SMEs with real-time inventory management and optimization, enhancing operational efficiency (Dalokay *et al.*, 2005; Gürsoy, 2020).

The first study combining JIT with simulation dates to the late 1990s, where the sequence established by the LM principle served as a foundation for subsequent simulation aimed at optimizing processes for optimal combinations (Aytug and Dag, 1999). Moreover, recent literature review along with case studies have demonstrated that JIT is integrated with DT technologies such as IoT, cloud computing, big data analytics, AI, and additive manufacturing (Peron, Alfnes and Sgarbossa, 2021). The study by Gürsoy *et al.*, (2021) on a hazelnut processing SME demonstrated how JIT principles were used to streamline process flow, ensuring that products were procured and available precisely when required by subsequent processes. The SME further optimized product distribution across its production line by integrating Kanban with big data analytics. While just-in-time (JIT) functions as a comprehensive principle encompassing various actions, Kanban serves as one of its primary tools, facilitating its implementation (Holweg, 2007; Bicheno and Holweg, 2016). Moreover, Kanban not only lays the groundwork for DT technologies in manufacturing but has also extended its influence on software development. For example, its principles have inspired the creation of workflow management tools like Kanbanize, illustrating Kanban's critical role in supporting DT adoption across industries, from manufacturing to software applications (Ahmad *et al.*, 2018; Kanbanize, 2021).

Kanban initially revolutionized inventory and workflow management, laying the foundation for efficient workflow processes as outlined in Section 2.3.5. In manufacturing SMEs, Kanban is often integrated with DT technologies like IoT where sensors and RFID are used to track Kanban cards (Shima *et al.*, 2022). More specifically, Kanban facilitates the adoption of DT technologies, with Kanban-based workflows serving as foundational elements for DT applications; for example, a Turkish manufacturer initially implemented a Kanban system, which is later integrated with a software and IoT to digitizing the management of parts (Güven, 2022). Furthermore, the e-Kanban system has been in use for nearly two decades. For instance, a case study dating back to 2005 highlighted a Turkish manufacturer's adoption of a Kanban system integrated with big data analytics in an e-Kanban system (Dalokay *et al.*, 2005). This integration enabled the identification and storage of frequently used parts closer to the shop floor, thereby reducing travel time for parts. In recent research by Gürsoy (2020) a Turkish furniture company implemented an e-Kanban system, which served as a foundation for the company's digital transformation. It also facilitated the adoption of additional digital transformation technologies, where the company was able to establish a framework that ultimately allowed for real-time information display within the system and shifted towards fully automated manufacturing processes integrated with Enterprise Resource Planning (ERP) systems. Hence, through e-Kanban flow principle lays a foundation for IoT and other DT technologies. Hence, as the ability and understanding of Kanban and flow techniques allow classification of work but also digital transformation in the respect that real-time work follow up and tracking can be made.

Overall, the SEM results align with literature studies dating back to the 1990s, which highlight the extensive use of the JIT principle and its integration with DT technologies to streamline manufacturing processes (Aytug and Dag, 1999; İşler, 2000). Among the tools supporting JIT, Kanban stands out as the most widely utilized, playing a pivotal role in process optimization and DT integration. This includes applications like e-Kanban, which enhances efficiency by enabling real-time inventory management and workflow synchronization across various technologies (Dalokay *et al.*, 2005; Gürsoy *et al.*, 2021; Güven, 2022).

6.4.4. Standardised Work and Digital Transformation

Standardised work, often linked to Standard Operating Procedures (SOPs), is identified as important for DT technology adoption in Turkish SMEs, showing a strong correlation (factor loading of 0.863) with the LM construct. The LM principles positively impact the adoption of DT technologies within Turkish SMEs, as demonstrated by a coefficient of 0.36, with standard work being a key component of the LM principles. The primary benefit arises from standardized work practices, particularly when documented as Standard Operating Procedures (SOPs) which provide clear, sequential guidelines for operators, enabling them to effectively navigate new, complex, or emergency scenarios, which is especially valuable for SMEs (Bashatah and Sherry, 2021).

In line with the results, studies have emphasized the benefits of standardized work and SOPs in facilitating the adoption of DT technologies, such as integrating robotics and implementing advanced software solutions (Stadnicka and Antonelli, 2019; Marinelli *et al.*, 2021). For instance, in Turkish SMEs, the implementation of standardized work has been effectively combined with robotics and automation on welding lines, where robotics integration was supported by defining, setting, and implementing structured rules and operational frameworks (Akyar, 2012; Kaymakçı, 2023). Moreover, standardization in robotics adoption ensures consistent application of best practices through clear guidelines for task execution, tool usage, and workplace layout. This is particularly significant in robot-human collaboration, where such guidelines are critical for maintaining safety and efficiency (Stadnicka and Antonelli, 2019). In the context of SMEs, robotics adoption is pivotal in driving growth within the manufacturing ecosystem, fostering the development of customizable systems that meet SME-specific needs while offering both flexibility and adaptability (Zheng, Yang and Cheng, 2019; Hohnoki, 2020). Thus, examples from Turkish SMEs demonstrate that integrating standardized work with robotics not only improves operational efficiency but also establishes a robust foundation for SMEs to adopt and adapt to advanced digital transformation technologies (Akyar, 2012; Kaymakçı, 2023).

The principle of standardized work extends its positive impact to various technologies beyond robotics in Turkish SMEs. For example, an aluminium processing manufacturer has utilized big data analysis to address high defect rates, implementing enhanced process solutions through standardized SOPs (Apilioğulları, 2020). Similarly, Turkish manufacturer Arçelik has been actively standardizing digital transformation technologies, including big data and artificial intelligence, to facilitate their seamless integration across global factory operations (Özceylan and Prof, 2023). These examples, along with insights from other case studies and literature, illustrate that standardized work and SOPs are essential for enabling Turkish SMEs to adopt digital transformation technologies such as robotics, big data, and AI, while ensuring adaptability to complex tasks and operational environments. Thus, the adoption of standardized work among Turkish SMEs and large enterprises reinforces the findings that standardized practices are critical for successful DT integration.

6.4.5. Continuous Improvement and Digital Transformation

The empirical results demonstrate that continuous improvement supports the adoption of DT technologies, as reflected in its strong correlation with the LM construct, with items LM8 and LM9 having factor loadings of 0.836 and 0.874, respectively. In line with this result, the principle of continuous improvement plays a crucial role on the adoption of technologies, by systematically establishing and refining standards and objectives that are closely linked to the technology (Canbay and Akman, 2023). Continuous improvement principle in manufacturing operations focuses on achieving stable and capable processes through incrementally enhancing the processes and standards indefinitely (Philip, 2018).

The examples of continuous improvement principles aid in adopting DT technology are extensively available in Turkish manufacturers, where of the cases focus on Digital Twin technology. For instance, in a Turkish glass manufacturer, the data from shop floor is continuously collected and analysed for enhancement of process involving Digital Twin technology (Aydin *et al.*, 2024). Furthermore, Turkish SMEs aim to apply DT technologies with aid of continuous improvement to tackle the problems. As an example, job shop production scheduling in SMEs is a challenging where many require optimization to achieve shorter lead times and lower production costs (Choi, Hwang and Kim, 2023). To address this issue, Turkish manufacturing SMEs utilize simulations for scheduling, integrating real-time data with Lean Manufacturing principles such as continuous improvement and Just-In-Time (JIT) to enhance the effectiveness of simulations (Turker *et al.*, 2019). By leveraging real-time data, these companies use customer feedback to drive continuous improvement efforts, which are also incorporated into AI systems for predictive maintenance. Additionally, research in Turkey indicates that the tracking of KPIs in real-time data, aligned with continuous improvement principles, is essential not only for SMEs and manufacturers but also for other industries in adopting digital transformation technologies (Sayar and Yüksel, 2018; Üzmez and Büyükbeşe, 2021). The principles of continuous improvement have a synergistic relationship with digital transformation technologies in Turkey, benefiting each other. For instance, in a Turkish automotive manufacturer, Digital Twin technology has been used for continuous improvement, where the DT technology incrementally enhance the production process (Mendi, 2022).

Continuous improvement aiding the adoption of DT involves not only tracking production process statistics but also setting employee-related goals that focus on their skills and engagement (Tortorella *et al.*, 2021). This is also acknowledged in Turkey, a white goods manufacturer demonstrated that employees need to pursue continuous improvement in their skills, including lifelong learning and strong team-working abilities, for the successful adoption of digital transformation technologies (Demirbag and Yildirim, 2022). Additionally, the Turkish government supports the need for improving and tracking employee skills through Model Factories, which offers training and funding via KOSGEB to provide hands-on, experience-based learning on digital transformation technologies (Turkish Ministry of Industry and Technology, 2023b). Furthermore, it there are ways to track the progress made on DT journey that includes capability, skills and involvement of employees that is getting tracked by initiatives (Akarun *et al.*, 2018, p. 201). Hence, continuous improvement in adopting digital transformation technologies involves tracking both equipment and employee skills, supported by Turkish manufacturers and government-funded training (Turkish Ministry of Industry and Technology, 2023b; Demirbag and Yildirim, 2024)

Overall, the analysis of the Turkish SMEs along with empirical results exhibit that continuous improvement principles help the adoption of DT technologies. This support in Turkish SMEs primarily targets enhancing processes and standards, but it also extends to improving the skills and engagement of people involved in DT technology adoption (Canbay and Akman, 2023; Aydin *et al.*, 2024; Demirbag and Yildirim, 2024).

6.4.6. People and Teamwork and Digital Transformation

People and teamwork have been crucial aspects of LM, where respecting employees and involving them in production processes is essential for achieving improvements (Liker, 2020). The SEM analysis of this study indicates that this LM principle positively influences the adoption of DT technologies, with factor loadings of 0.848 (LM10) and 0.812 (LM11) linking People and Teamwork to the LM construct. These results align with the many studies completed by in DT, showing that collaboration and teamwork are counted as critical success factors for technology adoption (de Sousa Jabbour *et al.*, 2018; Tortorella *et al.*, 2021; Bhatia and Kumar, 2022; Saihi, Ben-Daya and As’ad, 2023). In Turkish manufacturers the importance of teamwork and involvement of employees in DT technology adoption process are documented in case studies. One notable example is a Turkish SME that manufactures automotive parts for OEMs in study presented by (Koç and Özkan, 2021). In this case, robotics was integrated into the manufacturing process to facilitate the visual detection of defects. It highlighted that teamwork was crucial during the adoption process, especially in the initial stages of usage.

Further, a study by Nicolás-Agustín, Jiménez-Jiménez and Maeso-Fernandez (2022) concluded that employee involvement and problem-solving abilities are crucial contributors to the successful adoption of DT technologies. It emphasized the role of HR strategies in engaging people in projects and decision-making and fostering a collaborative work environment to address the challenges posed by DT technologies. Engagement of employees, along with their suggestions and problem-solving skills, plays a crucial role in addressing the challenges posed by DT technologies (Bittencourt, Alves and Leão, 2019; Frank *et al.*, 2024). In line with this, a survey conducted on Turkish manufacturers including SMEs implementing DT technologies in their operations has revealed that employee involvement is a critical factor for the successful adoption of these technologies (Canbay and Akman, 2023). For instance, in the development and implementation of AI in manufacturing operations, there is an integration of human elements into the process (Hoch *et al.*, 2022). This involves finding a middle ground by incorporating activities that involve solely humans and solely AI.

Similar approach is employed in deploying various other DT technologies, including within the context of Turkish manufacturers. Research conducted in a Turkish manufacturer indicated that the viewpoints and problem-solving capabilities of employees are leveraged to implement robotic and automation technology for enhancing efficiency (Çiğdem, Meidute-Kavaliauskiene and Yıldız, 2023). Furthermore, the study highlighted that the degree of involvement of employees in the process directly impacts the utilization level of the technology in another example, the research by Demirbag and Yildirim (2024) focused on the skills and work practices of employees in the white goods manufacturing industry, one of the sectors with the highest digital maturity in Turkey. The research unveiled that the adoption of technology changes the skillsets and social interactions of employees, with teamwork and problem-solving emerging as key competencies expected from companies striving for digital transformation. Overall, these insights from the data and supporting literature emphasize the importance of employee engagement and problem-solving to navigate the complexities of digital transformation technologies in Turkish manufacturing setting.

In summary, the empirical results, supported by an analysis of Turkish manufacturers, highlight that people and teamwork are essential for the successful adoption of digital transformation technologies. The involvement of employees in the adoption process, along with their problem-solving skills and collaborative efforts, are identified as critical success factors for Turkish manufacturers, as demonstrated by various studies (Canbay and Akman, 2023; Çiğdem, Meidute-Kavaliauskiene and Yıldız, 2023; Demirbag and Yildirim, 2024).

6.5. Impact of Digital Transformation on Operational Performance

According to the SEM results, DT technologies have a positive impact on operational performance, with a path coefficient of 0.36, statistically significant at the *** level. Furthermore, each of the items of DT technology showed a strong correlation, with factor loadings ranging from 0.797 to 0.952. This indicates that adopting Digital Twin/Simulation, Big Data, Cloud Computing, Robotics, Automation, IoT, Artificial Intelligence, and Additive Manufacturing technologies has a positive impact on operational performance which leads to acceptance of Hypothesis H3. The only exception was Cyber-Physical systems, where the item was not supported due to data inconsistencies, as detailed in Chapter 5. This section analyses these results in the context of Turkish SMEs, with the upcoming subsections explaining each DT technology in detail.

Overall, these the empirical results align with numerous studies on SMEs illustrating the operational benefits of adopting DT technologies have been shown (Moeuf *et al.*, 2018; Masood and Sonntag, 2020; Dossou, Laouénan and Didier, 2022; Khin and Hung Kee, 2022). For instance, studies have shown that the application of DT technologies, particularly cloud computing and IoT, positively impacts operational performance metrics such as lead time and productivity (Moeuf *et al.*, 2018; Malodia *et al.*, 2023). Robotics and automation technologies are also employed in SMEs for operational benefits, such as reducing costs and increasing efficiency (Zhou *et al.*, 2022; Yang *et al.*, 2023). Due to these benefits, even SMEs specific manufacturing layouts have been developed to incorporate robotics for flexible manufacturing (Zheng *et al.*, 2019). In another example focusing on adoption of AI in manufacturing, predictive maintenance and machine-learning has been adopted in SMEs to improve quality and decrease lead-time in SMEs (Khan *et al.*, 2022; Pejić Bach *et al.*, 2023).

While numerous studies highlight the benefits of DT technologies in SMEs, it is essential to consider the country-specific context, particularly that of Turkish SMEs, when interpreting these results. For instance, the study by Muller *et al.* (2024) highlighted variations in the technologies employed, integration methods, and challenges faced by SMEs in developing countries. Similarly, Tortorella, Giglio and van Dun (2019) emphasized that the impact of Industry 4.0 adoption on operational performance depends heavily on the context, especially when combined with LM principles. Thus, while SME-specific factors are critical, country-specific dynamics also play a significant role in shaping the outcomes of DT adoption (Muller *et al.*, 2024).Evaluating operational performance benefits requires a focus on the intensity of technology adoption and the specific manufacturing ecosystem (Sommer, Proff and Proff, 2021) which, in this case, must be contextualized within the unique characteristics of Turkish SMEs.

Firstly, focusing the intensity of Turkey's DT technology adoption in manufacturing, the report made on Digital Transformation Index by TUBİSAD have shown that Turkish manufacturers have been increasing adopting DT technology between 2019-2022 (TÜBİSAD, 2023). When it comes to benefits, a study on Turkish SMEs focused on digital transformation maturity concluded that adopting DT technologies leads to higher quality, increased efficiency, and optimal labour use (Arslan and Şensoy, 2022). Another research findings indicate that digital transformation technologies in Turkish manufacturing have the potential to increase throughput by 3% and boost revenue by 200 billion TL (5.5 billion Euros) annually (Sağbaş and Gülseren, 2019). Hence, the studies done on Turkish manufacturing and specifically on SMEs indicate benefits on DT technology, and also high awareness and adoption of DT technologies amongst Turkish SMEs (Gergin *et al.*, 2019).

Secondly, one of the reasons for DT technology's positive impact on operational performance can be attributed to the Turkish government's efforts to alleviate the burdens associated with innovation and DT technologies (Olcay and Bulu, 2015; Direkci and Tirgil, 2016). DT technologies are often risky and expensive investments where SMEs can be reluctant and have low resources (Müller, Buliga and Voigt, 2018). A study shows that higher revenue in Turkish SMEs correlates with greater DT maturity (Arslan and Şensoy, 2022). This study also indicates that as cost and revenue-related obstacles are alleviated, DT maturity and usage increase, leading to operational benefits such as increased efficiency. Therefore, increased financial support for SMEs enhances their chances of achieving operational benefits, as government aid and legislation are crucial for the adoption and success of DT technologies (Ulas, 2019). One of the main reasons for alleviating these financial obstacles could be attributed to strong government support of application of DT technologies through KOSGEB (Sırkıntılıoğlu and Durukan, 2023). Many cost and operational barriers are overcome when it comes to DT technologies through government support, this is proven through many case studies (Sariisik, Demir and Ogutlu, 2022). Hence, showing the revenue and DT maturity link, support of government over the years has been an important reason of DT technologies leading to operational benefits in Turkish SMEs (Arslan and Şensoy, 2022).

Overall, the empirical data shows a strong positive correlation for each technology to the DT construct ranging from 797 to 0.952, which has a high path coefficient to the Operational Performance construct with 0.31. Hence, the empirical findings emphasize the importance of integrating digital transformation technologies to enhance operational performance in Turkish manufacturing SMEs, leading to the acceptance of hypothesis H3. The analysis needs to be done on focusing on country-specific context looking at technology adoption and support in the country (Tortorella, Giglio and van Dun, 2019; Muller *et al.*, 2024). Focusing on Turkish SMEs, the empirical results of this study are supported by the high DT index among Turkish manufacturers and studies that support improved operational performance in SMEs through adoption of DT technologies (Gergin *et al.*, 2019; Arslan and Şensoy, 2022). Also, strong support of Turkish government for SMEs, helps financial burdens and improves DT technologies on enhancement of operational performance (Ulas, 2019; Sariisik, Demir and Ogutlu, 2022; Sırkıntılıoğlu and Durukan, 2023). Consequently, the analysis of Turkish manufacturing SMEs aligns with the empirical results, and the following section will provide a detailed examination of each DT technology within the context of Turkish SMEs.

6.5.1. Simulation/Digital Twin and Operational Performance

The Simulation and digital twin technologies are shown to enhance operational performance, with factor loadings of 0.881 (DT1) and 0.952 (DT2) to the DT construct, which has a path coefficient of 0.36 to operational performance. This finding aligns with extant research demonstrating simulation and digital twin improve operational performance across various industrial applications globally (Sit and Lee, 2023; Dutta and Kumar, 2024). Focusing on Turkey, a survey of 425 manufacturers revealed that SMEs, particularly in the automotive, electrical and electronics, and machinery industries, frequently use simulation (Sarı, Güleş and Yiğitol, 2020). The use of simulation and digital twin can be explained in two prominent benefits regarding the opportunity to improve the product and risk-free test of optimisations (Mukherjee and DebRoy, 2019; Huang *et al.*, 2022; Tao, Zhang and Zhang, 2024). Research has shown in Turkey, even the amongst low and moderate digital twin and simulation is used where it is amongst the technologies that are aimed to invested upon (Kıyak, 2023).

Simulations and digital twins play a crucial role in enabling manufacturers to explore multiple scenarios and identify optimal solutions for product development and process improvements (Hohnoki, 2020; Choi *et al.*, 2021; Wang and Luo, 2021). These technologies allow iterations and optimizations to be conducted without the high costs associated with physical trials (Leng *et al.*, 2022). For manufacturers, especially SMEs facing financial constraints, simulation and digital twin technologies have become increasingly popular, not only among industry practitioners but also researchers (Ferreira, Armellini and De Santa-Eulalia, 2020; Michna and Kmieciak, 2020). In Turkey, digital twin applications are widely utilized across various manufacturing sectors (Ergüt, 2019; Aslan, 2022). For example, a case study conducted in a Turkish textile SME used a digital twin to digitize physical information, including machinery data, enabling problem detection and efficiency improvements (Koçak and Yildiz, 2022). In a more specific instance, a CNC machine was analyzed through a digital twin to reduce lead time (Cesur, Cesur and Aydoğan, 2023). Additionally, Turkish SMEs employ simulations to optimize workforce shifts and workload distribution (Bal, Gevrek and Demir, 2022; Görgün and Öztürk, 2023).

Alongside digital twin technology, the integration of simulations not only enhances existing processes but also provides a platform to test and validate innovative solutions to complex problems (Löcklin *et al.*, 2020; Savolainen and Urbani, 2021). For instance, a Turkish textile manufacturer employed digital twin technology to test manufacturing planning and workload scheduling recommendations, achieving better optimization (Bal, Gevrek and Demir, 2022). Additionally, digital twin technology is frequently utilized to support the adoption of other technologies, such as automation and robotics (Guerra-Zubiaga *et al.*, 2021; Ramasubramanian *et al.*, 2022). In this context, Turkish manufacturers have developed and tested automation control systems through digital twin applications to enhance production flexibility and boost productivity (Sahin, Taskin and Kartal, 2023). Furthermore, studies on Turkish SMEs have demonstrated that simulations significantly improve efficiency in planning and adopting robotic systems, particularly by enabling better modelling of human-robot interactions (Çoskun, 2020).

The extensive examples of these technologies in Turkish SMEs and their contributions to enhancing operational performance are well aligned with the empirical results, which highlight the positive influence of simulation and digital twin technologies in Turkey, as documented in various case studies (Bal, Gevrek and Demir, 2022; Cesur, Cesur and Aydoğan, 2023). Additionally, the literature emphasizes their role as a testing ground for the implementation of other DT technologies, such as robotics and automation (Sahin, Taskin and Kartal, 2023)

6.5.2. Big Data Analytics and Operational Performance

From the SEM analysis, it is shown that big data analytics play an important part in enhancing operational performance within Turkish SMEs, where big data represents a critical component of DT technologies, as evidenced by factor loadings of 0.835 (DT3) and 0.903 (DT4). Recent research supports these findings, particularly in the manufacturing sector, highlighting notable advancements such as improved operational efficiencies and reductions in lead times through the application of big data analytics (Sayginer and Ercan, 2020a) .In addition, the comprehensive study by Karaboga *et al.* (2023) which included more than 400 participants from a diverse range of industries, further showed that big data analytics not only on operational but also on financial performance such as return of investment for Turkish companies.

Further research highlights that while Turkish SMEs are increasingly adopting big data analytics to enhance operational performance and they encounter challenges such as a shortage of skilled personnel to analyse data, concerns about data privacy, and infrastructure limitations in implementing these technologies (Kiziltan, 2018). To address these issues, the Turkish government provides training programs, and local banks like Yapı Kredi offer advisory services, incentive programs, and financial support to facilitate the adoption of big data analytics, reflecting the ongoing commitment to supporting Turkish manufacturers (Yağcı, 2020). Thus, although SMEs face obstacles in adopting big data analytics, available support mechanisms help mitigate these challenges and sustain adoption. The benefits of this adoption are reinforced by empirical results, which demonstrate that big data analytics positively impacts operational performance (Karaboga *et al.*, 2023).

One of the main improvements of big data analytics for responsiveness and big data driven product development and its improvement on operational performance is extensively amongst manufacturers (Ali *et al.*, 2020; Wang *et al.*, 2022). In line with results, a recent survey has shown that 73 Turkish manufacturers show that 73% use big data for product development for operational benefits (Abubakar, Bozkurt and Kalkan, 2022). The manufacturers in Turkey are using data such as return rate, customer satisfaction and quality reports in big data analytics to develop their products (Demir and Kazançoğlu, 2020). For example, a manufacturer in textile sector has developed looking at fibre, colouring, and cost through big data analysis to decrease cost and quality (Sabir, 2020). In another example, an automotive parts manufacturer in collaboration with manufacturing SME used the data gathered from customers to optimise the front seat of a car (Altun *et al.*, 2022).

In summary, SEM results align with the literature concerning where Big Data helps operational performance for SMEs (Karaboga *et al.*, 2023). The use of Big Data among Turkish SMEs has been documented through research where main improvement is regarding the product although SMEs face problems regarding infrastructure and employee skill (Abubakar, Bozkurt and Kalkan, 2022).

6.5.3. Robotics/Automation and Operational Performance

According to SEM results, robotics and automation are essential components of DT technologies, with items DT5 and DT6 demonstrating strong factor loadings of 0.847 and 0.827, respectively. A review of the literature underscores their significant role, with numerous studies documenting their positive impact on efficiency and productivity in both academic research and industry practice (Stadnicka and Antonelli, 2019; Choi *et al.*, 2021). This importance is further highlighted by research on 185 manufacturing SMEs in Turkey, where respondents identified automated robotics as the most crucial DT technology for their operations (Yiğitol, Güleş and Sarı, 2020)

Confirming the results, Turkey presents numerous case studies highlighting the adoption of robotics and automation among its SMEs. According to the International Federation of Robotics (IFR), Turkey installed 3,300 robots in 2022, increasing the total number of operational robots to over 14,000 and ranking as the 5th largest in Asia for robot installations (Güner, 2019; IFR, 2023).Supporting this trend, one of the world's leading robotics companies, KUKA, offers specially designed, user-friendly, and cost-effective robotic automation systems tailored to address the budgetary limitations of Turkish SMEs (KUKA, 2024). In a recent case study, a Turkish agricultural machinery producer implemented robotics and automation systems to scale up production and reduce lead times, enabling them to meet growing market demand (KOSGEB, 2024b). Additionally, another study on Turkish SMEs emphasized that one of the primary benefits of robotics is the reduction in lead times and decreased reliance on labour, both of which improve operational efficiency (Varol and Kaygisiz, 2018). These examples illustrate the growing role of robotics in enhancing productivity and competitiveness among Turkish SMEs.

Despite the widespread recognition of the advantages of robotics and automation, studies also emphasize critical challenges related to cost and strategic planning, particularly for resource-constrained SMEs (Hypki *et al.*, 2023; Nagy, Lăzăroiu and Valaskova, 2023). High implementation costs often disqualify smaller firms from accessing the operational performance benefits associated with these technologies. SMEs, which typically operate with limited financial resources, may struggle to invest in robotics and automation, leaving them unable to capitalize on the significant efficiency and productivity enhancements that these technologies provide. However, the findings of this study indicate that Turkish SMEs have successfully mitigated the cost barrier, as evidenced by their strong adoption rates of robotics and automation technologies and the resulting operational performance improvements. This shift can largely be attributed to targeted government support. For example, in 2022, the Turkish government provided a total of $15 million in funding to 278 SMEs implementing automation and robotics in their manufacturing processes (KOSGEB, 2021). Additionally, government initiatives such as training programs, strategic planning support, and financial incentives specifically designed for robotics and automation adoption have played a critical role in helping SMEs overcome cost-related constraints (Sırkıntılıoğlu and Durukan, 2023). These efforts not only barriers but also empower SMEs to integrate advanced technologies into their operations and gain the operational benefits attached to DT.

In summary, robotics and automation are critical components of DT technologies, as evidenced by SEM results and numerous studies highlighting their positive impact on efficiency and productivity in Turkish SMEs. Despite challenges such as high implementation costs, Turkish SMEs have adopted robotics with government support, that includes funding, training programs, and strategic incentives. Hence, the governmental initiatives, represents a vital strategy for operational advancement in the context of Turkish SMEs. Further, the combination of empirical findings, literature support, and practical examples show the growing role of robotics and automation in enhancing operational performance of Turkish SMEs.

6.5.4. Cloud Computing Systems and Operational Performance

Cloud computing, with a factor loading of 0.835 (DT7) to the DT construct, is a critical component of DT technologies. Given the positive impact of DT on operational performance in Turkish manufacturing SMEs, cloud computing plays a significant role in driving these improvements. This result is further supported by recent research on Turkish SMEs, where a survey of 112 SMEs conducted by (Kaplancalı and Akyol, 2021) revealed that cloud computing significantly improves business performance, especially in terms of agility and efficiency. Additionally, cloud computing has been used to overcome international barriers in emerging markets like Turkey (Hosseini *et al.*, 2019). Similar findings have been observed in SMEs from other developing countries, such as a study on 244 SMEs in Jordan, which showed that adopting cloud computing reduced costs, improved flexibility, and enabled more efficient operations (Yaseen *et al.*, 2023).

The primary benefit of cloud computing for SMEs includes cost-effective storage solutions, decentralization, and easy access to information (Mourad *et al.*, 2020). Studies on Turkish manufacturing SMEs indicate frequent use of cloud computing, with 36% utilizing it for data storage, 9% for data analysis, 6% for software applications, and 8% for machine data access and storage (Yiğitol, Güleş and Sarı, 2020). Additionally, Turkish

SMEs employ cloud systems for production and workforce planning, optimizing operations and ensuring seamless access to critical information (Akyol et al., 2020). In the aviation and defence sectors, cloud computing is utilized for storing part information, enabling easy access and design modifications (Ho *et al.*, 2021; Yin *et al.*, 2023). Beyond manufacturing, cloud computing is widely applied by Turkish companies for tasks such as HR, finance, and auditing, where data is securely stored and efficiently analysed in cloud systems (Göktaş *et al.*, 2018; Buyruk Akbaba, 2019; Abdioğlu and Gülşen, 2022). Hence, in Turkish SMEs cloud computing not only improving manufacturing efficiency but has diverse applications across manufacturing, planning, and administrative functions.

One notable result found in literature is that the adoption of cloud computing by SMEs, and its impact on operational performance, is often hindered by hesitancy due to concerns about security and privacy (Kuyucu, 2011; Alsafi and Fan, 2020; Sayginer and Ercan, 2020a). These challenges are acknowledged as barriers to adoption, but SMEs, including those in Turkey, have taken proactive steps to reduce their negative impact by implementing measures like data encryption and routine security audits (Henkoğlu and Külcü, 2014; Yesilyurt and Yalman, 2016). These efforts, especially encryption methods help alleviate the concerns related to privacy and security (Kiesel *et al.*, 2023). Furthermore, local cloud companies have been established that allow personalisation and auditing for data for manufacturers in Turkey (Hammad *et al.*, 2023). Therefore, despite concerns about security and privacy, techniques such as encryption and security auditing have been implemented to enable SMEs to access cloud services (Abdulsalam and Hedabou, 2022).

Aligning with the findings of this research, the literature highlights that Turkish manufacturing SMEs achieve significant operational improvements through cloud computing, consistent with broader industry research (Kaplancalı and Akyol, 2021). Turkish SMEs adopt cloud computing for its benefits, including cost-effective storage, enhanced flexibility, improved efficiency, and optimized production and workforce planning (Akyol *et al.*, 2020; Yiğitol, Güleş and Sarı, 2020; Abdioğlu and Gülşen, 2022). While security and privacy concerns pose challenges, Turkish SMEs are addressing these barriers through measures such as encryption and security auditing, fostering broader adoption of cloud computing technologies (Henkoğlu and Külcü, 2014; Yesilyurt and Yalman, 2016; Sayginer and Ercan, 2020b).

6.5.5. Internet-of-Things and Operational Performance

The Internet of Things (IoT) positively impacts operational performance in Turkish SMEs, as indicated by the findings, with a factor loading of 0.845 to the DT construct, which, in turn, shows standardized path coefficient of 0.36 with operational performance. This demonstrates that IoT as part of DT technologies enable SMEs to enhance operational performance. This finding aligns with the current trends in the Turkish manufacturing ecosystem, where numerous trials and implementations of IoT technologies have been undertaken (Uslu *et al.*, 2019).

Supporting these findings, a study on Turkish SMEs examined six companies that improved operational performance through the adoption of IoT technologies, including the use of smart sensors (Sırkıntılıoğlu and Durukan, 2023). Turkish SMEs benefit significantly from the affordability of sensors, which enhances their ability to optimize operations (Kirci, 2015; Ağseren and Şimşek, 2024). Recently, Turkish white goods manufacturer Vestel implemented an IoT-powered forklift operation system to improve efficiency (IHA, 2023). Similarly, Arçelik, another leading white goods manufacturer, has been embedding IoT systems into its devices and manufacturing processes since 2018, using IoT-powered sensors to monitor dyeing processes and optimize energy efficiency across its plants (NTV, 2018; Arçelik, 2024). In addition, SMEs in Turkey receive support for IoT adoption through initiatives like the MEXT Industrial IoT Experience, a government-backed program providing hands-on exposure to industrial IoT technologies to accelerate digital transformation (AutomationTR, 2022; MEXT, 2022). Beyond manufacturing, IoT projects in Turkey have been implemented across various sectors for years, such as Smart Water meters, which enable remote water reading and management for cities (Turk Telekom, 2017). These examples show the growing adoption and benefits of IoT technologies in Turkey.

In terms of operational benefits from IoT adoption, studies indicate that IoT can significantly reduce labour and operational costs for SMEs, although challenges in implementation can sometimes lead to unnecessary expenses and time inefficiencies (Uslu *et al.*, 2019). A key driver of IoT adoption in Turkey is the affordability and widespread availability of sensors, as demonstrated in a food production SME where sensors monitor cattle and human movement, as well as air and water conditions, to improve production efficiency (Kirci, 2015). Additionally, RFID systems, a prominent IoT application, have been widely adopted in Turkish manufacturing to streamline inventory management, reducing excess stock, lowering holding costs, and enhancing supply chain efficiency (Yaman and Bayğın, 2020; Yasa and Akdag, 2021; Taşkın *et al.*, 2022).

Overall, IoT positively impacts operational performance in Turkish SMEs, as supported by both empirical findings and literature. The literature highlights how Turkish manufacturers utilize affordable sensors to monitor processes, improving efficiency and reducing costs. Government initiatives and industry-led implementations, such as those by Vestel and Arçelik, further demonstrate the widespread adoption and significant operational benefits of IoT across Turkish industries.

6.5.6. Artificial Intelligence and Operational Performance

The findings presented in the previous section demonstrate that the use of artificial intelligence (AI) in Turkish SMEs positively influences operational performance as part of the DT construct, with DT10, representing AI, showing a factor loading of 0.797. Supporting this, recent studies on AI have shown that it significantly improves performance, particularly in terms of reducing cost, inventory and optimizing operational efficiency (Albayrak Ünal, Erkayman and Usanmaz, 2023; Ronaghi, 2023). Research conducted on over 100 Turkish SMEs revealed that AI is widely utilized and ranks as the fourth most deployed DT technology (Yildirim *et al.*, 2023).

As an example of AI applications in Turkey, a study by (Aktepe, Yanık and Ersöz, 2021) highlighted a Turkish manufacturer in the machinery sector, producing spare parts for construction machinery, successfully integrating AI for demand forecasting, which improved inventory and production management while significantly enhancing operational efficiency. Another key area is machine learning for predictive maintenance, where AI is widely employed by manufacturers across industries such as aerospace, automotive, and healthcare (Çınar *et al.*, 2020). For instance, a Turkish manufacturer using AI-driven predictive maintenance can identify machine-related issues in advance, enabling preventative actions that improve both product quality and cost efficiency (Ayvaz and Alpay, 2021).

Expanding on machine learning, Turkey has adopted various technologies not only in production processes but also in products. For example, Türk Traktör, a major tractor manufacturer, has invested in Agrovisio, a machine learning-based system that supports farmers in decision-making (Türk Traktör, 2024). Using AI-driven image processing, Agrovisio evaluates satellite imagery and weather data to map cultivated areas, predict crop yields, identify optimal harvest times, and monitor plant health, significantly improving agricultural productivity (Ergül, 2023). Similarly, Baykar, a leading Turkish defense manufacturer, employs AI and machine learning in its aircraft systems to detect landmarks and calculate tilt, vertical positioning, and orientation angles, ensuring operational reliability even in the absence of GPS or other navigation tools (Baykar, 2024). Beyond manufacturing, Turkish SMEs leverage machine learning techniques to anticipate financial distress up to three years in advance, providing early warnings that help mitigate risks of bankruptcy (Aker and Karavardar, 2023). These examples demonstrate Turkey's widespread integration of machine learning across industries,

Empirical results and literature show that AI has a positive influence on operational performance through reducing costs, improving efficiency, and optimizing processes in Turkish SMEs (Albayrak Ünal, Erkayman and Usanmaz, 2023; Ronaghi, 2023; Yildirim *et al.*, 2023). Machine learning, a key AI application, enhances predictive maintenance, demand forecasting, and decision-making across various industries (Ayvaz and Alpay, 2021; Ergül, 2023).

6.5.7. Additive Manufacturing and Operational Performance

Additive manufacturing positively influences DT technologies, as evidenced by the empirical results, where DT11, representing additive manufacturing, has a strong factor loading of 0.806 to the DT construct. This relationship is further validated by findings in the literature and industry practices, which emphasize additive manufacturing as a transformative advancement in manufacturing, offering significant cost reductions and lead-time efficiencies (Niaki and Nonino, 2017; Blakey-Milner *et al.*, 2021).

Supporting these findings, a study of 226 Turkish manufacturers revealed that adopting additive manufacturing not only reduces costs but also boosts competitive advantages (Turkcan, Imamoglu and Ince, 2022). The empirical results align with the extensive use of additive manufacturing and 3D printing technologies in Turkey, which have been employed since 1993 and play a vital role in the automotive and aerospace industries (Özsoy *et al.*, 2020). Beyond manufacturing, Turkey has expanded the use of 3D printing into the medical field, such as in the production of orthodontics (Ertürk, Ayyıldız and Erdöl, 2021), and during the COVID-19 pandemic, it was utilized to manufacture healthcare supplies to address shortages (Advincula *et al.*, 2020). These examples demonstrate the versatility of additive manufacturing in various industries, highlighting its extensive use in Turkey.

Additive manufacturing is primarily used for creating prototypes through 3D printing, offering flexibility in part geometry and production time, which addresses the challenges of manufacturing complex components and structures (Kalender *et al.*, 2019). In Turkey, this technology is widely employed by aerospace and automotive companies to produce polymer and metal prototypes, often for product certification purposes (Özsoy *et al.*, 2020). Additionally, 3D printing enables product customization, allowing manufacturers to create tailored parts and adapt processes for both mass customization and large-scale production (Garrett, 2014; Spahiu *et al.*, 2020). Thus, additive manufacturing supports the creation of prototypes, complex productions, and customized solutions, making it an essential tool for industries like aerospace and automotive, which represent approximately 18% of the companies participating in this study and align with the sectoral distribution shown in Table 5.3

Overall Additive manufacturing positively impacts DT technologies supported with literature and industry practices that highlight its role in reducing costs, enhancing efficiency, and boosting competitiveness (Niaki and Nonino, 2017; Turkcan, Imamoglu and Ince, 2022). Widely used in Turkey since early 90s, additive manufacturing supports diverse industries such as aerospace, automotive, and medical fields, enabling prototype creation, complex production, and customized solutions (Kalender *et al.*, 2019; Özsoy *et al.*, 2020).

6.6. Comparative discussion with prior studies

6.7. Chapter Conclusion

This chapter analysed the empirical findings and hypotheses in the context of existing literature and industry practices. It begins with an overview of the results, where the conceptual model demonstrated a strong structural fit, supported by indices such as Chi-square ratio (1.582), RMSEA (0.053), GFI (0.841), and CFI (0.954). In the following sections, Turkish manufacturing landscape and SME characteristics are thoroughly examined, and a detailed analysis of each hypothesis is provided, supported by relevant literature to interpret the empirical findings.

The acceptance of Hypotheses H1 and H2 confirms that institutional effects ($\beta = 0.18$, $p < 0.01$) and LM principles ($\beta = 0.36$, $p < 0.001$) positively influence the adoption of DT technologies. Hypothesis H1, encompassing mimetic, coercive, and normative pressures, yielded positive results, diverging from some literature findings, particularly for coercive and normative pressures, which are often associated with neutral or negative effects in other contexts. For Hypothesis H2, a detailed analysis highlights how each LM principle supports DT adoption, with examples from the Turkish manufacturing sector and SMEs, showcasing their practical applications and benefits. Hypothesis H3 validates the strong positive impact of DT technologies on operational performance ($\beta = 0.36$). This finding highlight that despite operational and financial challenges, government initiatives, including funding programs and model factories, play a critical role in helping Turkish SMEs overcome these barriers and achieve performance improvements.

Chapter 7: Conclusion

7.1. Chapter Introduction

In the conclusion chapter, the findings of the research are summarised while the research questions and objectives are revisited. This is followed by the of the study's outcomes, emphasizing the key contributions and implications from theoretical, academic, and managerial standpoints. The chapter concludes by discussing the limitations of the study followed by recommendations for future research.

7.2. Research Outcomes

This section revisits the research questions and objectives, showing how they were addressed and how the study's goals were met. As highlighted in Chapter 1, the study focused on three primary aims which will be revisited in this section in detail, explaining how each of them has been achieved. The first research aim '*To introduce and empirically verify a conceptual framework incorporating links between LM principles, DT technologies and operational performance*', was partially addressed in Chapter 5 through the conceptual model developed from the comprehensive literature review in Chapter 3. The literature review laid the theoretical groundwork necessary for building the conceptual framework and identified a significant gap in the existing literature that is the need for the introduction and validation of a comprehensive framework (Bittencourt, Alves and Leão, 2020). After constructing the conceptual model, three hypotheses (H1, H2, and H3) are introduced, as displayed in Table 3.5. The validation of the framework was completed through statistical analysis using the data gained from the survey questionnaire. This data was analysed using SEM which statistically tested and confirmed the proposed framework. Confirmatory Factor Analysis (CFA) verified the measurement model, with goodness-of-fit indices (Chi-square ratio = 1.468, RMSEA =0,048, GFI =0.842, CFI = 0.963, IFI =0.963, NFI=0.894), while reliability and validity tests confirmed internal consistency as well as both convergent and discriminant validity (Hair, Black and Babin, 2010), as detailed in Chapter 5. As a result, the proposed conceptual model was statistically validated, successfully addressing the first research aim of establishing a framework that links LM principles, DT technologies, and operational performance in SMEs.

With the conceptual framework introduced and statistically verified, the first research question revisited RQ1: "*How do Lean Manufacturing principles affect the adoption digital transformation technologies within small and medium-sized manufacturing enterprises (SMEs) in Turkey?*". To empirically test this, IBM AMOS software is utilized to develop a SEM and analyse the relationships between the constructs outlined in the conceptual framework. Specifically, this includes testing the hypothesis H2: "*LM Principles have a positive effect on Digital Transformation technologies*". SEM results showed that LM principles had a strong positive correlation with DT technologies, with coefficients are 0.36 and p-value indicating a highly significant level (***, significant at the 0.001 level). P-value above shows that the correlation between LM and DT are not random chance but statistically strong (Andrade, 2019). The findings were consistent with current research that emphasized the LM principle's role in supporting DT technology adoption (Bittencourt, Alves and Leão, 2020; Powell, Morgan and Howe, 2021). Therefore, in response to the research question, the statistical analysis confirmed that Lean Manufacturing principles positively influence the adoption of DT technologies, supporting the acceptance of Hypothesis H2. In conclusion, the completion of the necessary CFA and SEM results successfully achieved the first research aim, thereby addressing the first research question.

The positive correlation between LM principles and Digital Transformation technologies in SEM directly addresses the second research question, RQ2: "*Which Lean Manufacturing principles positively the adoption of Digital Transformation technologies within Turkish manufacturing SMEs?*". In the SEM analysis done in Chapter 5, the factor loadings for each LM principle ranged from 0.792 to 0.956 reflecting the strength of the relationship between observed variables and the latent construct (Tavakol and Wetzel, 2020). This shows that each LM principle demonstrated a strong positive relationship with the construct, which in turn showed a strong correlation with the DT principles. Consequently, each LM principle examined showed a strong correlation to the DT principles, also achieving the second research aim: "*To empirically assess and identify which LM principles has a positive impact on adoption of DT technologies in Turkish SMEs".* To support the statistical findings and provide a more comprehensive answer to RQ2, the statistical results are further examined in detail in Chapter 6, the Discussion chapter, which explores how LM principles support the adoption of DT technologies in Turkish SMEs. As an example, consistent with the SEM findings, waste elimination facilitated the adoption of DT technologies by streamlining processes and visualizing the process layout for these technologies (Wang *et al.*, 2021), where many examples of this integration have been observed in Turkish SMEs (Gürsoy, 2020; Demirbag and Yildirim, 2022; Parlak, 2022). This analysis is also reinforced by the literature review, which includes case studies highlighting the combined application of LM and DT technologies together (Yilmaz *et al.*, 2022). Thus, the second aim was accomplished through statistical analysis, with the SEM results highlighting which LM principles had positive factor loadings and a strong correlation with DT technologies. This is further reinforced by examples, case studies, and context from Turkish SMEs discussed in Chapter 6, which provides a detailed overview of how LM principles positively impact Digital Transformation technologies from the perspective of Turkish SMEs.

Similarly, the results of the SEM Model are used to answer the second research question that is "*How does adoption of Digital Transformation (DT) technologies affect operational performance outcomes in SMEs within the Turkish manufacturing landscape?*". In relation to this, Hypothesis H3 tested the relationship between DT and operational performance as hypothesized in the conceptual model: "*Digital Transformation technologies have positive effect on operational performance*". The findings demonstrated that DT principles positively impact operational performance, with all DT technologies except one showing a positive influence on DT adoption. More specifically, the DT construct showed a strong positive correlation of 0.360 with the operational performance construct, with a highly significant p-value, as detailed in Chapter 5. All DT technology items included in the analysis had factor loadings ranging from 0.797 to 0.952 within the DT construct, indicating that each item positively contributed to Digital Transformation. Chapter 6 further explored how the adoption of these technologies enhances operational performance within the context of Turkish SMEs. For example, the implementation of robotics has been associated with reduced lead times due to the increased operational speed of robots, as demonstrated in Turkish SMEs (Koch, Manuylov and Smolka, 2021). The statistical analysis supported by recent literature in Chapter 6 achieve the second objective that is "*To investigate and identify which DT technologies lead to operational performance improvement in SMEs*". Overall, the third aim and second research question are answered through the acceptance of H3 Hypothesis and SEM analysis and further explained with literature in Chapter 6.

The theoretical lens of this research is based on institutional theory, with one of its aims being "*to identify the external pressures that affect the adoption of DT technologies in Turkish SMEs*". The theoretical framework developed in Chapter 3 incorporates external pressures in form of institutional effects in relation to DT technologies, building on and expanding frameworks from prior literature (Ketokivi and Schroeder, 2004). This relationship between institutional effects and DT technology was hypothesized in the conceptual framework through H1: "*Institutional Effects have a positive effect on Operational Performance*" To test the H1 hypothesis, SEM results were used, which showed that institutional effects positively influence DT technology adoption, with a standardized path coefficient of 0.18 ($p < 0.01$). The institutional effects were categorized into three pressures: mimetic, normative, and coercive. Each item within these categories demonstrated factor loadings ranging from 0.682 to 0.794, reflecting a good representation of the institutional effects construct. Each pressure was analysed with specific examples from the Turkish manufacturing SME context in Chapter 6, such as coercive pressures from KOSGEB, mimetic pressures from competitors, and normative pressures from suppliers, as illustrated by cases (KOSGEB, 2022; TOFAS, 2022; Şişecam, 2022, 2024; Sırkıntılıoğlu and Durukan, 2023; Arçelik, 2024). Hence, through empirical analysis and detailed discussion, the external pressures that are mimetic, normative and coercive influencing DT technology adoption were identified and analysed, successfully achieving the aim of the research.

Overall, the research has met all its aims regarding providing and empirically validating a conceptual framework and describing the analysis of how LM principles improve DT technology adoption and how this, in turn, improves operational performance. Furthermore, answers to each research question and support for the hypotheses in the conceptual framework have been provided. In the next section, contributions of the research along with its originality and novelty are explained.

7.3. Novelty and Contribution

The contributions of the research are from achieving the research aims and answering the research questions. In this section original contribution and research novelty is analysed, where novel contribution refers to adding a unique contribution to an existing body of knowledge highlighted (Thesaurus, 2024).

In terms of theoretical contribution, this research has contributed to theory by expanding the institutional theory to include contingencies through developing a theoretical framework. One of the drawbacks of institutional theory has been identified as broadness, lack of specificity and not including contextual factors, where companies act or respond the external pressures in complex environments how this affects the organisations (Krajnović, 2017; Fogaça, Grijalvo and Neto, 2022). These can profoundly influence how companies adapt, strategize, and operate in response to institutional demands especially when it comes to innovation and digitisation (Geels, 2020; Gupta *et al.*, 2020; Sony and Aithal, 2020). The framework proposed in this study addresses this gap by integrating specific contingencies in manufacturing landscape such as company size and sector which shape organizational behaviour in complex settings (AlNuaimi *et al.*, 2022; Fogaça, Grijalvo and Neto, 2022). Through the validation of this framework and accompanying literature this study has not only demonstrated a more refined theoretical approach that accounts for how context-specific influences affect organizational responses. Hence, this study makes a novel contribution to the theory by expanding the institutional theory and its framework to be adaptable to diverse environments, particularly in dynamic sectors such as manufacturing as outlined as gap in literature by recent research (Sony, 2020; Fogaça, Grijalvo and Neto, 2022).

Adding on to the institutional theory, one of the key contributions and a surprising finding of this research is the identification of the positive impact of all institutional effects, especially on coercive and normative effects for adoption of DT in Turkish SMEs. This contribution is significant for two main reasons: firstly, due to the scarcity of existing data as although there has been prior research on institutional effects, limited attention has been given to developing countries where previous research highlighted there are important differences (Adebanjo *et al.*, 2013; Yawar and Kauppi, 2018; Kelling *et al.*, 2021; Kauppi and Luzzini, 2022). More importantly, previous studies have yielded inconsistent findings regarding the impact of external pressures in different contexts, with no clear consensus on their impact on DT. In some cases, normative pressures were perceived as negative influences on DT, and some studies suggested they had no significant impact (Lin and Sheu, 2012; Zhu, 2016; Čater *et al.*, 2021; Kuo, Chen and Yang, 2022). Additionally, coercive effects have often been viewed as neutral in studies in where it does not directly lead to DT or has a negative effect in emerging countries (Beta and Ogunmokun, 2023; Zhou and Zheng, 2023). Hence, this study contributes to the literature by demonstrating the positive influence of institutional factors and by expanding the existing body of knowledge especially in developing country context where more research is needed (Kelling *et al.*, 2021; Kauppi and Luzzini, 2022). Through this, it offers deeper insights into the mechanisms driving this positive impact such as government incentives within a country-specific context, providing guidance for similar research. Future research can build on these insights by exploring how specific institutional pressures can be leveraged for DT technology adoption in SMEs.

Another important contribution is empirically validating a comprehensive conceptual framework that links on the relationship between DT technologies, LM principles and operational performance. One of the gaps of literature mentioned by prominent researchers are regarding lack of large enough sample to allow an empirical analysis (Bittencourt, Alves and Leão, 2019; Pagliosa, Tortorella and Ferreira, 2019; Tortorella, Miorando and Cawley, 2019; Rossini *et al.*, 2023). Additionally, the framework is based on institutional and contingency theories, which are commonly used in LM and DT research but have not been combined in a conceptual framework before (Kostova, Roth and Dacin, 2008; Gupta et al., 2020; Szász et al., 2021; Jiao, Yang and Cui, 2022b). This integration of two theories in LM and DT context resulted in a distinctive conceptual model but also allowed a more comprehensive model including LM principles and DT technologies. Consequently, the creation and validation of this framework, along with its extension on the DT and LM relationship, constitute a novel contribution to the field.

A futher contribution is regarding empirically validating influence of LM principles on DT technologies. While a positive impact has been mentioned in the literature for different contexts, explaining how LM helps the adoption of DT technologies (Helleno *et al.*, 2014; Powell, Morgan and Howe, 2021), empirical validation has always been limited to small sample sizes, which do not allow for comprehensive statistical analysis (Pagliosa, Tortorella and Ferreira, 2019; Tortorella *et al.*, 2019; Ciano *et al.*, 2021; Dixit, Jakhar and Kumar, 2022). To address this gap, data were collected from Turkish SMEs to analyse the impact of LM principles on DT technologies using SEM for statistical analysis. The statistics demonstrated that LM principles aid the adoption of DT technologies and provided data on which specific LM principles are beneficial, as analysed and supported by literature in detail in Chapter 6. Thus, this study makes a novel contribution by empirically validating the positive impact of LM principles on DT technologies and explaining how LM principles facilitate the adoption of DT technologies.

In addition, this research has made a novel contribution in the context of DT technologies impact on operational performance, especially in manufacturing SMEs in Turkey, a developing country. When it comes to DT technologies available research is limited in developing countries like Turkey in comparison to developed countries (Shqair and Altarazi, 2022). There has been limited research and gap in the topic of impact of DT technologies in developing countries (Raj *et al.*, 2020; Atieh, Cooke and Osiyevskyy, 2023). Therefore, this study contributes to the literature by demonstrating the impact of DT technology adoption in Turkish SMEs, which possess typical characteristics and resources of a developing country (Gergin *et al.*, 2019). Furthermore, by focusing on Turkey, this research adds to country-specific literature and provides evidence for developing countries by addressing the unique challenges and opportunities faced by Turkish SMEs in their digital transformation journey.

Furthermore, this research contributes to expansion of research in DT and Turkish SME context. While the empirical analysis for institutional effects have been available in different context (Lin and Sheu, 2012; Goh and Goh, 2019; Gupta *et al.*, 2020; Jiao, Yang and Cui, 2022), this research has made a novelty regarding investigating and consequently showing positive impact of institutional effects on DT adoption in Turkish SME context. This research not only validates the positive influence of LM principles on DT adoption but also extends institutional theory by highlighting how institutional pressures, categorized as mimetic, coercive, and normative (Gupta *et al.*, 2020), can drive DT transformation in SMEs. By providing empirical evidence and validation, this research expands the understanding of institutional effects, offering valuable insights for both academic researchers and practitioners in the field, especially working in SMEs.

7.4. Implications of the Study

There are several managerial, policy and theoretical implications that will be highlighted in the below sections.

7.4.1. Managerial and Policy Implications

In terms of managerial implications, this research provides valuable insights for managers to establish and guide their DT technology adoption processes. It offers strategies and guidelines to enhance the likelihood of successful DT adoption, helping managers navigate challenges and make informed decisions to align technologies with organizational goals. The low success rate of DT initiatives has been highlighted as a main problem where the highlighted as 10-30% (Bucy, 2016; Ramesh and Delen, 2021). Firstly, to improve the success rate, this research has provided empirical evidence and supporting case studies on Chapter 5 on which LM principles aid the adoption of DT technologies offering managers actionable insights to shape their DT strategies. Managers aiming to adopt a DT technology in a manufacturing company can leverage specific LM principles to guide their efforts. For example, this research highlights waste elimination as a LM principle that positively influences DT technologies. The literature review further identifies Value Stream Mapping (VSM) as a widely used waste elimination tool in conjunction with DT technologies (Yilmaz *et al.*, 2022). Studies show that VSM helps visualize and streamline DT technologies like automation and robotics, enabling process optimization (Chiarini and Kumar, 2020; Wang *et al.*, 2021). By integrating VSM, managers can organize and refine processes, improving the organization's readiness for technological integration. Hence, this research offers valuable guidelines for managers, outlining which LM principles are beneficial and how they can be implemented based on insights from the discussion and literature review.

Secondly, this research enhances managerial decision-making by supplying empirical evidence on which LM principles provide positive effect on DT technologies and consequently operational performance improvements. Furthermore, Pfeffer and Sutton (2006) pointed out the importance of evidence-based management, where managers use evidence in form of research, empirical evidence, and analysis together with their intuition and experience. In practice, high-quality decisions should integrate critical thinking with the available evidence (Barends, Rousseau and Briner, 2014). This study provides managers with empirical evidence and a detailed analysis, as presented in Chapter 6, highlighting which LM principles enhance DT technologies and improve operational performance, thereby supporting their decision-making processes. Additionally, presenting evidence of benefits and case studies can assist managers in securing support from top management and investors for DT initiatives and LM principles (Baba and HakemZadeh, 2012; Antunes *et al.*, 2023). This is especially important to support managers in developing country SMEs considering DT technology adoption where the data is limited (Shqair and Altarazi, 2022). Consequently, through this study managers are equipped with the necessary evidence to strengthen their decision-making processes, ensuring they have the tools to advocate for DT initiatives and attract investor support, thereby facilitating the DT technologies.

Thirdly, on the SME context, this research has provided customised information for managers and governments in developing countries. One of the gaps in literature is highlighted was lack of research for developing countries where prior research such as by Shqair and Altarazi (2022) evaluated Industry 4.0 in SMEs and argued that there is a lack of country-based studies for developing to compare the results. These similarities between the developing countries have been identified by Raj *et al.* (2020) from limited resources to infrastructure that limit DT adoption. Adding on to this research, this study provides valuable insight and support for managers in developing countries, by providing a country-specific analysis. For example, while investment in automation and robotics may pose a challenge for resource-limited manufacturing SMEs (Norberto Pires, 2009), this research provides evidence that such investments can enhance operational performance, including improved lead times. Additionally, by presenting case studies of manufacturing SMEs applying robotics and detailing their support mechanisms like those provided by KOSGEB (Demir, 2019; KOSGEB, 2023c), this research enables managers in developing countries to navigate their journey more effectively towards adopting digital transformation. Overall, this research equips managers and governments in developing countries with tailored insight and strategic guidance on DT initiatives in manufacturing SMEs.

The study also has policy implications, particularly for institutions like KOSGEB, which supports Turkish SMEs with financing, training, and resources for LM principles and DT technologies (Sevinç and Eren, 2019). These government institutions can leverage the findings of this study to fine-tune their strategies by focusing on LM principles that have a proven positive impact on DT technology adoption. For example, this study has shown that Flow/JIT aids DT technology adoption where supporting literature shows that it helps categorize work tasks and is often combined with DT technologies (Phumchusri and Panyavai, 2015; Raog, Kenneth Michael and Sriram, 2019). Consequently, institutions like KOSGEB can integrate LM principles, such as training, into their digital transformation support programs for SMEs. This approach facilitates a more effective and efficient allocation of resources in DT adoption efforts, leveraging the positive impact of LM principles on digital transformation. This research equips governments with the information needed to efficiently allocate efforts and resources towards supporting the most effective LM principles to help SMEs adopt DT technologies.

More specifically, Turkish government can also see the impact of their external pressures, legislation, and their support on adoption of DT technologies. As part of the conceptual model, institutional effects are also examined on the adoption of DT technologies, which showed that government encouragement has a positive impact on DT technology adoption. For example, in section of coercive pressures, the interpretation of Turkey's Digital Transformation has led to a comment on tax relief to SMEs (TÜBİSAD, 2023). This provides a good layout to continue the support, especially the results show that the adoption of DT technologies lead to aimed operational performance improvement that the Turkish government aimed for. These findings underline the effectiveness of the strategies and policies implemented by Turkey to encourage DT adoption. Moreover, they suggest that the support and funding provided to SMEs adopting DT technologies are yielding positive outcomes, reinforcing the value of these initiatives (KOSGEB, 2021) Furthermore, this has a wider impact, where the repeating this study in different countries can test the effectiveness of the governments support on SMEs for adoption of DT technologies.

Overall, the managerial implications of this study equip managers with actionable insights and evidence-based strategies and to enhance DT adoption and improve operational performance and get top management support.

Meanwhile, the policy implications provide guidance for institutions like KOSGEB and governments to optimize support programs and external pressures, ensuring more effective adoption of DT technologies.

7.4.2. Theoretical Implications

There are several theoretical implications of this study. Firstly, this research challenges isomorphism attached to institutional theory. Isomorphism assumes that organizations, in response to external pressures will behave in similar ways (DiMaggio and Powell, 1983). However, the pressures and responses can vary significantly among different groups such as company size, sector and country as supported by previous literature (Kauppi, 2022, p. 202; Ali and Johl, 2023). While dealing with traceability requirement in a sector like food manufacturing, for example ISO 22000 that deals with food traceability does not necessarily require digital traceability (Allata, Valero and Benhadja, 2017). Hence, when it comes to traceability many SMEs take a less expensive approach by adopting paper-based systems while large enterprise use blockchain in Turkey (Kiliç *et al.*, 2020; Kayikci *et al.*, 2022; Alptekin, 2024). This shows that for the same normative pressure, the different context due to the size of the company, the response of the company would be different. Thus, while the research recognizes the principles of institutional theory and the tendency for to behave similarly under certain conditions, it shows that responses are not universally consistent across the board. Instead, they can depend on group characteristics, where contingencies such as company size must be considered (Bhatia and Kumar, 2023). Therefore, this research challenges isomorphism amongst large groups and asks for the need to account for these contingencies to gain a better understanding of how organizations respond to external pressures.

Through the integration of contingency theory, this research has allowed expansion of theoretical framework attached to institutional theory. It has been one of the key theoretical lenses that had been a core part of DT research (Hinings, Gegenhuber and Greenwood, 2018; Gupta *et al.*, 2020; Fogaça, Grijalvo and Neto, 2022). While previous studies have proposed similar frameworks, none have been empirically validated to demonstrate the integration (Vilkas *et al.*, 2022). By constructing and validating this theoretical framework, the study addresses a significant theoretical gap, offering a comprehensive model that integrates LM principles and DT technologies, an area where previous research lacked empirical support and sufficient sample sizes (Pagliosa, Tortorella and Ferreira, 2019; Rossini *et al.*, 2019). This conceptual framework contributes to theory by integrating diverse constructs, such as institutional effects, LM principles, DT technologies, and operational performance, within a single model, offering empirical validation. This validation not only strengthens the theoretical foundations but also opens opportunities for applying the framework to other fields where institutional theory alone may not be sufficient. Furthermore, the framework allows connection between theory with practical applications, offering a reliable, empirically tested framework for assessing theory in real complex conditions.

This study contributes to the ongoing theoretical discussion on institutional theory, which often fails to fully address the unique challenges and responses companies have in rapidly changing contexts such as digital transformation and innovation (Gupta *et al.*, 2020; Kelling *et al.*, 2021; Akenroye *et al.*, 2024). The findings of this study indicate that, although companies facing the same external pressures may display certain similarities, demonstrating the relevance of institutional theory, this framework alone may be insufficient in dynamic settings and areas like digital transformation and innovation, as highlighted by previous research (Geels, 2020; Fogaça, Grijalvo and Neto, 2022). These rapidly evolving contexts require flexibility and responsiveness, which institutional theory does not inherently include. For example, SMEs often face financial constraints when adopting DT technologies (Ghobakhloo and Iranmanesh, 2021). In Turkey, however, SMEs can access government funding through programs like KOSGEB (KOSGEB, 2021), a transformational support mechanism that would have been overlooked without considering company size or location as a contingency variable. This highlights the importance of including variables to enhance the theoretical model. While institutional theory is essential for understanding organizational responses to external pressures, it needs to be combined with relevant contingency factors to better reflect the dynamic topics like digital transformation.

This research makes a significant theoretical contribution by conceptualizing and validating a theoretical model for the adoption of DT technologies, drawing on and building upon insights from previous literature (Ketokivi and Schroeder, 2004; Bokrantz *et al.*, 2020; Vilkas *et al.*, 2022). It expands on the theoretical model for DT technologies and their relationship with LM principles, as initially suggested by Ketokivi and Schroeder (2004). By expanding and validating the theoretical model, this research enhances the understanding of how organizations adapt and remain flexible in a DT context, when facing similar external pressures. This contribution offers a framework, which can aid future researchers in exploring the interplay of institutional and contingency theories, not only within DT and LM fields but also across other areas of organizational behaviour.

Overall, this study makes significant theoretical contributions by challenging the isomorphic assumptions of institutional theory, showing that organizational responses to external pressures vary based on contingency factors such as company size. It develops and empirically validates a comprehensive conceptual model linking institutional effects, LM principles, DT technologies, and operational performance, addressing gaps in previous research. This integrated framework bridges institutional and contingency theories, providing a foundation for future research in dynamic contexts like digital transformation and innovation, as well as other areas of organizational behaviour.

7.5. Research Limitations and Future Research

There are number of limitations can be highlighted in this study. On theoretical level, the theoretical model can be expanded to include more contingency variables. This study has included company size and sector as one of the most used in research (Szász *et al.*, 2021; Pozzi, Rossi and Secchi, 2023). To expand on this there are other variables that can be included in the framework in future. For example, leadership and organisational structure can be part where some research on contingency theory already exists on different contexts (Csaszar and Ostler, 2020; Bhatia and Kumar, 2023). By including these variables, future studies could develop a more comprehensive theoretical model, offering insights into the complex and contextual factors shaping DT adoption, ultimately improving the relevance and applicability of the findings for diverse organizational settings. By limiting the number of contingencies considered, the study may have overlooked important organisational characteristics, the study may have overlooked certain organisational characteristics that influence DT adoption. This could have introduced bias by constraining the ability to capture the full range of factors shaping the responses, thereby limiting the depth and robustness of the findings

The study focused to bring DT technologies adoption and its consequential effect on operational performance, it is limited to include the relationship between LM principles and operational performance variables. Furthermore, LM principles have inherent effect to operational performance. The relationship between LM principles and DT technologies are still ongoing in the academia and industry where focus on their synergy (Powell, Morgan and Howe, 2021). While this study focuses on how LM principles facilitate DT technology adoption, it also opens opportunities to investigate the reverse scenario how DT technologies might positively influence the adoption of LM principles. This reciprocal relationship could provide a richer understanding of how these two frameworks complement each other. By not including the reverse relationship, the findings may present a one-directional view that potentially limits the completeness of the model. Hence, future research can expand the conceptual model to consider the interrelation between LM principles and operational performance which to strengthen the theoretical model.

One limitation of this research is its generalizability. This study focuses on SMEs, with a significant representation from medium-sized companies, reflecting the broader SME population. As a result, the findings may not be directly applicable to large enterprises, although the framework has potential for broader application across different company sizes, which could be explored in future research. Additionally, this research delivers country-specific insights from SMEs in a developing country, filling a notable gap (Shqair and Altarazi, 2022), but creating a geographical limitation. The research focuses on the companies in Turkey which potentially introduced cultural and institutional bias, as the specific environment and market conditions in Turkey. Therefore, conclusions cannot be extended beyond developing countries and context-dependence should be considered when interpreting the findings. Nonetheless, the conceptual model has been tested and verified through this study, suggesting it could be adapted for a more generalized company population and other locations in future research. To address the geographical constraints, future studies could replicate this research in various countries to also add on the research focusing on DT technology adoption differences between developed and developing nations (Raj *et al.*, 2020). Furthermore, since institutional effects are country-specific and external pressures vary (Krell, Matook and Rohde, 2016), this framework could be tested in different regions to explore how institutional pressures differ across various geographies.

As another limitation, the study restricted the scope to manufacturing operations in factories. However, the use of LM principles and DT technologies go beyond manufacturing operations to supply chain (Moyano-Fuentes, Sacristán-Díaz and Martínez-Jurado, 2012; Fatorachian and Kazemi, 2021; Garcia-Buendia *et al.*, 2021). This may have introduced bias towards production-focused scenarios and limited the scope for understanding how LM and DT interact in other areas. Hence, the scope and content of the study can be adapted or expanded to include other internal company functions such as accounting and supply chain elements such as logistics.

In terms of future research, the theory of the research could we further expanded by including more contingency variables. As current research includes company size and sector, incorporating additional contingency variables such as leadership style and organisational structure could be included to capture a broader range of contextual influences such as organisational culture, competitiveness and ownership structure (Szász *et al.*, 2021; Pozzi, Rossi and Secchi, 2023). Given the explanatory nature of this research, the inclusion of additional variables would also enhance its capacity to identify and explain complex relationships in DT adoption. Expanding the range of contingencies would also strengthen the framework through improve its relevance across diverse organisational settings.

Future studies could extend the theoretical framework by integrating complementary theories that address limitations of institutional theory in dynamic contexts. For example, the resource-based view (RBV) a widely used theoretical lens for studying LM and DT, could be incorporated to account for internal organisational resources and capabilities as explanatory variables (Ali and Johl, 2023; Aripin *et al.*, 2023). This would strengthen the framework and enable a deeper analysis of DT adoption. Incorporating such theoretical perspectives would provide a more holistic understanding of how external pressures, internal characteristics, and capabilities interact, thereby addressing institutional theory's limitations in accounting for SMEs in different settings and offering a stronger basis for explaining DT adoption in varied contexts.

To build on from this research, how specific LM principles facilitate adoption of DT technologies can be further explored through qualitative research. While the conceptual model has been proven, the depths of the specific relationships between LM principles, DT technologies and operational performance require further exploration (Bittencourt, Alves and Leão, 2019). One of the limitations of a purely quantitative methodology is that it does not capture deeper, contextual insights. Complementary qualitative findings could have revealed insights such as underlying motivations for DT and LM adoption, implementation challenges, and manufacturing specific factors. Future research could benefit from a more detailed examination on the specific relationships between LM principles and DT technologies that incorporate qualitative methods such as case studies, focus groups, or interviews with SMEs. Qualitative methods would allow researchers to capture the lived experiences, organisational contexts, and decision-making processes that underpin DT adoption. For example, this research has shown that simulation has a positive effect on DT adoption, and its underlying dynamics could be examined further through interviews with SMEs. Such interviews could provide detailed insights into how companies use LM practices to support DT initiatives, revealing the organisational, cultural, or industry-specific factors that shape these interactions. These approaches could provide deeper insights into the mechanisms on how LM principles specifically aid the adoption of DT technologies, potentially deeply analysing the issue of low DT technology adoption in SMEs. This further research could validate these mechanisms in practice and help to form basis for practical guidelines, training programmes, and policy measures that help SMEs to use LM more effectively to achieve successful DT.

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Appendix A: Questionnaire

Section 1: Demographic

1. Where is the company based?
   ☐ Turkey
   ☐ Others (specify) __________

2. How many employees does your company have?
   ☐ ≤ 10
   ☐ ≤ 50
   ☐ ≤ 100
   ☐ >250
   ☐ ≤ 250

3. What is your company's annual turnover (€)?
   ☐ ≤ 2 million
   ☐ ≤ 10 million
   ☐ ≤ 50 million
   ☐ > 50 million

4. What is your current position within the company?
   ☐ CEO/ Director/ General Manager/Factory Manager
   ☐ Mechanical/Design Engineer
   ☐ Quality Manager/Engineer
   ☐ Manufacturing Manager/Engineer
   ☐ Others (specify) __________

5. What industry does your company operate in?
   ☐ Textile
   ☐ Oil, Chemical,
   ☐ Plastic,
   ☐ Glass,
   ☐ Metal and Metalworking
   ☐ Machinery, Aerospace, Automotive and Parts,
   ☐ Food, Beverage
   ☐ Wood, Furniture, Paper
   ☐ Others (specify) __________

6. What type of manufacturing process does your company utilize?
   ☐ Batch*
   ☐ Continuous**
   ☐ Job Shop***
   ☐ Others (specify) __________

****Batch manufacturing** refers to a production process where a group of similar products is made together in a specific quantity or "batch" before transitioning to a different product or setup.*

*****Continuous manufacturing** is a method where products are made without interruption, often in a continuous flow, allowing for high-volume production of standardized items.*

****Job shop manufacturing** involves producing custom or unique products based on specific customer orders, typically with varying requirements and production processes.*

Section 2: Questionnaire

1. To what extent do you agree with the following statements on Digital Transformation?

Please use the following scale: 1=Strongly disagree, 2=Somewhat disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5= Strongly Disagree

Our competitors who have adopted digital transformation technologies have greatly benefitted.	1	2	3	4	5
Our competitors who have adopted digital transformation technologies are favourably perceived within the same industry and customers.	1	2	3	4	5
The government/KOSGEB requires us to adopt digital transformation technologies	1	2	3	4	5
Our customers require us to adopt digital transformation technologies	1	2	3	4	5
Our customers have adopted digital transformation technologies	1	2	3	4	5
Our suppliers have adopted digital transformation technologies	1	2	3	4	5

Lean manufacturing principles *include just-in-time, elimination of waste, continuous improvement, standard work, built-in quality, respect for people & teamwork. Lean manufacturing principles use aid of tools such as value stream mapping, kanban, kaizen, visual controls, shop-floor walks, problem-solving techniques such as 8D technique.*

*****Digital Technologies** include simulation, digital twin (eg. 3D virtual model), big data analytics, automation, robotics, cloud computing, internet of things and additive/advance manufacturing.*

2. To what extent do you agree with the following statements regarding the use of Lean Manufacturing principles in your company?

Please use the following scale: 1=Strongly disagree, 2=Somewhat disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5= Strongly Disagree

Our company use Value Stream Mapping to minimise waste	1	2	3	4	5
Our company identify wastes and solve problems by generating new ideas	1	2	3	4	5
We monitor quality issues through charts in shopfloor	1	2	3	4	5
We use fishbone type diagram to identify the cause of quality issues	1	2	3	4	5
For production control, we use signals/cards/ticket where production is based on demand of preceding process	1	2	3	4	5
Products are classified into groups with similar routing/processing requirements	1	2	3	4	5
There are standard operating procedures for manufacturing operations	1	2	3	4	5
Up-to-date charts showing defect rates, key performance indicators, progress and next job activity are displayed on the shop floor	1	2	3	4	5
We track our progress against our stated goals/KPIs	1	2	3	4	5

Shopfloor employees are key to problem solving teams	1 2 3 4 5
Shop floor employees lead product/process improvement effort	1 2 3 4 5

* KPI (Key Performance Indicators)

3. To what extent do you agree with the following statements regarding the adoption of digital transformation technologies in your company?

Please use the following scale: 1=Strongly disagree, 2=Somewhat disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5= Strongly Disagree

We have a 3D digital or CAD drawing of our product.	1 2 3 4 5
We use advance simulations for process display and improvement	1 2 3 4 5
We use advance data analytics for product development	1 2 3 4 5
Our company monitor production in real-time	1 2 3 4 5
Our company use automation for production processes	1 2 3 4 5
Our company use robotics for our manufacturing processes	1 2 3 4 5
Our company is using cloud computing systems to store and manage production data	1 2 3 4 5
Machines in our factory can collect data on process, equipment etc through cyberphysical systems.	1 2 3 4 5
Machines in our factory are connected to each other and receive feedbacks	1 2 3 4 5
Our company uses predictive maintenance for machine maintenance	1 2 3 4 5
Our company uses 3D printing/additive manufacturing in production processes	1 2 3 4 5

4. To what extent do you agree with following statements regarding the operational performance benefits realized due to adoption of digital transformation technologies?

Please use the following scale: 1=Strongly disagree, 2=Somewhat disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5= Strongly Disagree

Reduced inventory	1 2 3 4 5
Productivity improvement	1 2 3 4 5
Lead or cycle time reduction	1 2 3 4 5
Improved product quality	1 2 3 4 5
Increase in profit	1 2 3 4 5
Reduced costs of production	1 2 3 4 5

Bölüm 1: Demografik Bilgiler

1. Nerede çalışıyorsunuz?
   ☐ Türkiye
   ☐ Others (specify) __________

2. Şirketinizin kaç çalışanı var?
   ☐ ≤ 10
   ☐ ≤ 50
   ☐ ≤ 100
   ☐ >250
   ☐ ≤ 250

3. Firmanızın yıllık cirosu (€) nedir?
   ☐ ≤ 2 Milyon
   ☐ ≤ 10 Milyon
   ☐ ≤ 50 Milyon
   ☐ > 50 Milyon

4. Şirketteki mevcut pozisyonunuz nedir?
   ☐ CEO/ Direktör/ Genel Müdür/Fabrika Müdürü
   ☐ Makine/Tasarım Mühendisi
   ☐ Kalite Müdürü/Mühendisi
   ☐ Üretim Müdürü/Mühendisi
   ☐ Diğer __________

5. Firmanız hangi sektörde faaliyet gösteriyor?
   ☐ Tekstil,
   ☐ Kimya,
   ☐ Plastik,
   ☐ Cam,
   ☐ Makine, Otomotiv ve Parçaları,
   ☐ Gıda, İçecek,
   ☐ Ahşap, Mabilya, Kağıt
   ☐ Diğer __________

6. What type of manufacturing process does your company utilize?
   ☐ Parti Tipi/Batch Flow*
   ☐ Seri Üretim**
   ☐ Özel/Proje Tipi Üretim***
   ☐ Diğer __________

****Toplu üretim,** benzer ürünlerden oluşan bir grubun belirli bir miktarda veya parti halinde üretildiği üretim sürecini ifade eder.*

*****Sürekli üretim,** ürünlerin standart öğelerin yüksek hacimli kesintisiz ve sürekli bir akışla üretildiği üretildiği yöntemdir.*

******Özel üretim,** belirli müşteri siparişlerine dayalı olarak, genellikle değişen gereksinimler ve üretim süreçlerine dayalı özel ürünler üretmeyi içerir.*

Bölüm 2: Anket

1. Aşağıdaki ifadelere ne derece katılıyorsunuz:

Lütfen aşağıdaki ölçeği kullanın: 1=Kesinlikle katılmıyorum, 2=Kısmen katılmıyorum, 3=Ne katılıyorum ne katılmıyorum, 4=Kısmen katılıyorum, 5= Kesinlikle katılmıyorum

Dijital dönüşüm teknolojilerini benimseyen rakiplerimiz bundan büyük fayda sağladı.	1	2	3	4	5
Dijital dönüşüm teknolojilerini benimseyen rakiplerimiz sektör ve müşteriler içerisinde olumlu algılanıyor.	1	2	3	4	5
Devlet/KOSGEB dijital dönüşüm teknolojilerini benimsememizi talep ediyor	1	2	3	4	5
Müşterilerimiz bizden dijital dönüşüm teknolojilerini benimsememizi istiyor	1	2	3	4	5
Müşterilerimiz dijital dönüşüm teknolojilerini benimsedi	1	2	3	4	5
Tedarikçilerimiz dijital dönüşüm teknolojilerini benimsedi	1	2	3	4	5

**Yalın üretim ilkeleri; tam zamanında üretim, israfın ortadan kaldırılması, sürekli iyileştirme, standart çalışma, yerleşik kalite, insana saygı ve ekip çalışmasını içerir. Yalın üretim ilkeleri, değer akışı haritalaması, kanban, kaizen, görsel kontroller, atölye yürüyüşleri, 8D tekniği gibi problem çözme teknikleri gibi araçların yardımını kullanır.*

****Dijital Dönüşüm Teknolojiler arasında simülasyon, dijital ikiz (örneğin 3D sanal model), büyük veri analitiği, otomasyon, robotlar, bulut bilişim, nesnelerin interneti ve additif üretim yer almaktadır.*

2. To what extent do you agree with the following statements regarding the use of lean manufacturing principles in your company?

Lütfen aşağıdaki ölçeği kullanın: 1=Kesinlikle katılmıyorum, 2=Kısmen katılmıyorum, 3=Ne katılıyorum ne katılmıyorum, 4=Kısmen katılıyorum, 5= Kesinlikle katılmıyorum

Şirketimiz israfı en aza indirmek için Değer Akışı Haritalaması kullanıyor	1	2	3	4	5
İsrafları tespit ederek ve yeni fikirler üreterek sorunları çözeriz.	1	2	3	4	5
Kalite sorunlarını üretim bölümündeki çizelgeler aracılığıyla izliyoruz	1	2	3	4	5
Kalite sorunlarının nedenlerini belirlemek için balık kılçığı diyagramı kullanırız.	1	2	3	4	5
Üretim kontrolünde önceki prosesin talebine göre sinyaller, kartlar veya biletler kullanıyoruz.	1	2	3	4	5
Ürünler benzer üretim süreçlerine göre gruplar halinde sınıflandırılır	1	2	3	4	5
Üretim işlemleri için standart çalışma prosedürleri vardır	1	2	3	4	5
Üretimde güncel kalite, KPI, üretim durumunu gösteren çizelgeler var	1	2	3	4	5
Belirtilen hedeflerimize ve KPI'larımıza göre performansımızı sürekli olarak değerlendiririz.	1	2	3	4	5

Üretim bölümü çalışanları, sorun çözme ekiplerinin anahtar üyeleridir.	1 2 3 4 5
Üretim bölümü çalışanları ürün ve süreç iyileştirme çabalarına liderlik ederler.	1 2 3 4 5

*yalın üretimde 7 temek israf: hatalı üretim, fazla üretim, fazla stok, bekleme, gereksiz işler, gereksiz taşıma/lojistik, gereksiz fiziksel hareket ve kullanılmayan insan yeteneğidir.

** KPI (Key Performance Indicators), Türkçe'de Temel Performans Göstergesi anlamına gelir ve bir hedef kriteri olarak kullanılır

3. Dijital dönüşüm teknolojilerinin şirketinizde kullanılmasına ilişkin aşağıdaki ifadelere ne ölçüde katılıyorsunuz?

Lütfen aşağıdaki ölçeği kullanın: 1=Kesinlikle katılmıyorum, 2=Kısmen katılmıyorum, 3=Ne katılıyorum ne katılmıyorum, 4=Kısmen katılıyorum, 5= Kesinlikle katılmıyorum

Ürünümüzün 3D dijital veya CAD çizimi bulunmaktadır.	1 2 3 4 5
Proses gösterim ve iyileştirilmesi için ileri düzeyde simülasyonlar kullanıyoruz.	1 2 3 4 5
Ürün geliştirmede ileri düzey veri analitiklerinden faydalanıyoruz.	1 2 3 4 5
Şirketimiz üretimi gerçek zamanlı olarak izlemektedir.	1 2 3 4 5
Şirketimiz üretim süreçleride otomasyon kullanmaktadır.	1 2 3 4 5
Şirketimiz imalat süreçlerinde robotlar kullanmaktadır	1 2 3 4 5
Şirketimiz üretim verilerini saklamak ve yönetmek için bulut bilişim sistemlerini kullanmaktadır.	1 2 3 4 5
Fabrikamızdaki makineler birbiri ile bağlıdır ve geri bildirim alabilir.	1 2 3 4 5
Fabrikamızdaki makineler, süreç, ekipman vb. hakkında veri toplayabilen siber-fiziksel sistemlerle donatılmıştır.	1 2 3 4 5
Şirketimiz makine bakımı için önleyici bakım tekniklerini kullanmaktadır.	1 2 3 4 5
Şirketimiz üretim süreçlerinde 3D print/eklemeli imalat teknolojilerini kullanmaktadır.	1 2 3 4 5

4. Dijital dönüşüm teknolojilerinin kullanılmasıyla gerçekleşen operasyonel performans artışlarına yönelik aşağıdaki ifadelere ne ölçüde katılıyorsunuz?

Lütfen aşağıdaki ölçeği kullanın: 1=Kesinlikle katılmıyorum, 2=Kısmen katılmıyorum, 3=Ne katılıyorum ne katılmıyorum, 4=Kısmen katılıyorum, 5= Kesinlikle katılmıyorum

Stoğumuz azaldı	1	2	3	4	5
Üretkenliğimiz arttı	1	2	3	4	5
Teslimat veya üretim döngü süresi azaldı	1	2	3	4	5
Ürün kalitesi arttı	1	2	3	4	5
Karlılığımız Arttı	1	2	3	4	5
Üretim maliyetleri azaldı	1	2	3	4	5

Appendix B: Introductory Letter

Hello,

I am a Doctoral Researcher from Brunel University London, and my PhD thesis focuses on how Lean Manufacturing can help Digital Transformation in Small and Medium Enterprises (SMEs). As part of this mentioned research, I will be doing an online questionnaire about Lean Manufacturing and Digital Transformation in SMEs. This questionnaire aims to understand SMEs level of knowledge on Lean Manufacturing and Digital Transformation and if/how external pressures and Lean Manufacturing is being used to implement Digital Transformation.

If you are working in a manufacturing SME in manufacturing or quality related department, would you be able to complete it?

You can find the Participant Information Sheet in the survey link prior to the survey. This questionnaire has been approved by the Brunel Research Ethics Committee.

Merhaba,

Ben Brunel Üniversitesinde bir Doktora Öğrencisiyim ve Doktora tezim olan Yalın Üretim ve Dijital Dönüşümün küçük ve orta ölçekteki üreticilerdeki durumunu anlamak için online anket yapıyorum. Bu anket Türkiye'deki Yalın Üretim ve Dijital Dönüşüm bilgi ölçeğini anlamaya ve dış etkenler ve yalın üretim'in dijital dönüşüme yardım edip etmediğini anlamayı amaçlıyor.

Eğer belirtilen firmalarda yönetim, üretim ya da kalite fonksiyonundaysanız formu doldurabilir misiniz?

Katılımcı bilgilendirme dosyasısını anketten önceki linkte bulabilirsiniz. Bu anket Brunel Research Etik Kurulu tarafından onaylanmıştır.