

**MANAGING OPERATIONAL UNCERTAINTY IN
MANUFACTURING WITH
INDUSTRY 4.0 AND 5.0 TECHNOLOGIES:
A MODIFIED NEO-CONFIGURATIONAL
PERSPECTIVE**

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by

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Abstract

The manufacturing sector is a significant economic multiplier due to its strong connections to the economy's downstream and upstream output sectors. It supports the notion that manufacturing drives industrialisation and can serve as the primary engine for growth and employment creation. Despite its importance, the manufacturing sector has challenges associated with diminishing size and lack of competitiveness, especially in countries such as South Africa. These challenges are exacerbated by prevailing operational uncertainties that negatively impact manufacturing firms. Literature on operational uncertainty, fourth and fifth industrial revolution technologies and organisational learning show several interrelated theoretical and methodological gaps, highlighting three empirical and theoretical gaps as well as two methodological gaps.

Six propositions were developed to investigate the research objectives. This was done using a multi-method quantitative design based on the post-positivist paradigm, with data collected from 22 experts (expert survey) and 262 firm representatives (firm survey). The results of the study confirmed that operational uncertainty is a multi-dimensional construct with a reflective model for dimensions and reflective-reflective for higher-order

construct. This means that for the dimensions, the indicators can be added or excluded in the formation of the dimension. The same is also true for construct, operational uncertainty.

The results of the present study also confirm that operational uncertainty is a norm in the manufacturing industry with a Manufacturing Operational Uncertainty Index (MOUI) = 0.752, indicating the range of futures. This posits that it is difficult to divide these futures into a discrete and exhaustive set of possibilities due to the complexity of conditions (variables) at play. Industry 4.0 and 5.0 technologies and their capabilities can manage the operational uncertainty dimensions with these technologies capable of scenario planning and supply chain integration (SPSI), flexible production and mass customisation (FPMC), real-time system and process monitoring and response (RPMR), root cause analysis and sustainable solutions (RCAS). These technologies are mainly artificial intelligence (AI), Internet of Things (IoT), big data analytics (BDA) and to a less extent advanced robotics (ARB), blockchain and augmented and virtual reality (ARVR). Organisation learning is also an effective causal condition to incorporate in managing operational uncertainty with Industry 4.0 and 5.0 technologies.

The study has both theoretical and methodological contributions. In theory, it advanced the modified neo-configuration theory, while the methodology provided an Manufacturing Operational Uncertainty Index and integrated fsQCA with fuzzy decision-making trial and evaluation laboratory (DEMATEL), and structural equation modelling partial least square (PLS-SEM). This research study is important since the recognition and dissemination of subjects within the field of operations management hold great significance for firms, which is contingent upon their sector of operation. This research offers valuable insights for academia, policymakers, and the manufacturing sector. It helps with their activities to effect meaningful change in day-to-day business operations, allowing for more effective progress in the subject area, and promoting practical, real-world issue-solving.

Keywords: Operational uncertainty; Industry 4.0 and 5.0 technologies; organisational learning; sustained performance; qualitative comparative analysis (QCA), modified neo-configurational perspective

Declaration

I declare that the Thesis titled *Managing Operational Uncertainty in Manufacturing with Industry 4.0 and 5.0 Technologies: A Modified Neo-configurational Perspective*, which I hereby submit for the degree of Doctor of Philosophy at Rhodes University, is my own work. I also declare that I have not previously submitted this thesis for a degree at this or any other tertiary institution and that all the sources I have used or quoted have been indicated and acknowledged by complete references.



Matolwandile Mzuvukile Mtotywa (*signed*)

*In memory of my dad, Pakade Mtotywa
(11 April 1941 – 1 December 2020)
and
my mom, Nontobeko Mtotywa
(29 November 1942 – 25 October 2017)*

Ku Vuyi, Gqwesa, Ngqiqo noQaqamba
Ingwe izidla ngamabala ngenxa yenu, ndinibulela ngazoz'ibini
Maz'enethole

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Acronyms and Abbreviations

AEFC	Efficiency
AfCFTA	African Continental Free Trade Area
AI	Artificial intelligence
AIC	Akaike's information criterion
ADM	Additive manufacturing (3D printing)
APRO	Profitability
ARB	Robotics and advanced robotics
ARVR	Augmented and virtual reality
ASUS	Sustainable practices
AVE	Average variance extracted
B2B	Business-to-business
BDA	Big data analytics
BCC	Blockchain
BIC	Bayesian information criterion
BRIC	Brazil, Russia, India, China
BRICS	Brazil, Russia, India, China, and South Africa.
BRICS+	Brazil, Russia, India, China, and South Africa, plus others (Egypt, Ethiopia, Iran, and the United Arab Emirates)
BBC	BRICS Business Council
CAIC	Consistent AIC
CB-SEM	Covariance-based structural equation modelling
CCD	Change in customer demand
CCP	chemical and petroleum
cfQCA	Comparative fuzzy-set qualitative comparative analysis
CKM	Compromise knowledge management
CLC	Cost of living-driven consumer behavioural change
CI	Confidence Interval
CIP	Competitive Industry Performance
CMV	Common method variance
COVID-19	Coronavirus disease 2019
csQCA	Crisp-set qualitative comparative analysis
CTA	Confirmatory tetrad analysis

DEA	Data envelopment analysis
DEMATEL	Decision-making trial and evaluation laboratory
DMUs	Decision-making units
EN	Normed entropy statistic
EPL	Entrenchment power of large firms
ESS	Energy stability and security
EU	European Union
FAB	Food and beverage
FCV	Fluctuation of currency value
FIMIX	Finite mixture
FPMC	Flexible production and mass customisation
fsQCA	Fuzzy-set qualitative comparative analysis
G7	Group of Seven
GDP	Gross Domestic Product
geoQCA	Geographic qualitative comparative analysis
GPT	Geopolitical tensions
GNU	Government of National Unity
GWB	Generational work behaviour and ethics
HOC	Higher-order constructs
HQ	Hannan-Quinn criterion
HTMT	Heterotrait-Monotrait criterion
ICP	Increase in the cost of production (ICP)
IMF	International Monetary Fund
IMT	Indicators of Industry 4.0 and 5.0 technologies capabilities
INUS	Insufficient but Non-redundant part of an Unnecessary but Sufficient condition.
Industry 1.0	First industrial revolution
Industry 4.0	Fourth industrial revolution
Industry 5.0	Fifth industrial revolution
IIoT	Industrial Internet of Things
IoE	Internet of Everything
IoT	Internet of Things
IRT	Industrial revolution technologies (Industry 4.0 and 5.0)
IT	Information Technology

LnL	LogLikelihood
LV	Latent Variable (LV)
LOC	Lower-order construct
M	Mean
MAR	Market access restriction
Mdn	Median
MDL	Minimum description length
MOUI	Manufacturing Operational Uncertainty Index
MV	Manifest Variables
mvQCA	Multi-value qualitative comparative analysis
N	Number (frequency)
NCA	Necessary condition analysis
NEC	Normalized entropy criterion
NFI	Non-fuzzy index
OM	Operations management
OLN	Organisational learning
OT	Operational Technology
OPU	Operational uncertainty
OPU2	Operational uncertainty with causal conditions only
PCV	Process capability and variations
PDT	Pandemic turbulence
PLS-SEM	Structural Equation Modelling Partial Least Squares
PEHS	Protective ecosystem (human and systems)
PPI	Producer price inflation
PUI	Policy uncertainty index
PRU	Policy and regulatory uncertainty
PwC	PricewaterhouseCoopers
QCA	Qualitative comparative analysis
QCP	Quantum computing
QoP	Quality of the product
QR	Quick response (codes)
RLA	Restricted labour availability and productivity
RFID	Radio-frequency identification
RCAS	Root cause analysis and sustainable solutions

RII	Relative importance index
RPMR	Real-time system and process monitoring and response
SARB	South African Reserve Bank
SCD	Supply chain disruption
SCIC	Supply chain integration and collaboration
SD	Standard deviation
SFW	Skills for future industrial work
SPF	Sustained performance
SPFP	Scenario planning and future prediction
SDGs	Sustainable development goals
SME	Small and medium enterprises
SPSI	Scenario planning and supply chain integration
SRMR	Standardised Root Mean Square Residual
Std.	Standard
TIVA	Trade in Value Added Database
tQCA	Temporal Qualitative Comparative Analysis
UNIDO	United Nations Industrial Development Organisation
USA	United States of America
VAR	Variable
VR	Virtual reality
WEF	Water, energy and food
WIOD	World Input-Output Database
WoS	Web of Science

Terms and Definitions

Term	Description	Reference
Causal condition	Causal Condition is the independent factor or dimension used to explain the outcome.	Schneider and Wagemann (2012); Iannacci and Kraus, (2022)
Ceteris paribus	Ceteris paribus, a Latin phrase meaning "all other things being equal," is a concept used across various fields to isolate the effect of one variable by holding others constant	Sheridan (2014)
Configuration	Combination of conditions that describes a group of hypothetical or empirically observed cases	(Schneider and Wagemann (2012)
Causal Asymmetry	Causes that lead to the presence of an outcome of interest that may be different from those that lead to the absence of the outcome	Fiss (2011)
Causal Condition	Independent variable - a factor considered necessary or sufficient to explain a particular outcome	Schneider and Wagemann (2012)
COVID-19	COVID-19 is a disease caused by the SARS-CoV-2 coronavirus, which usually spreads between people in close contact	Arias-Maldonado, (2020) World Health Organization (2020)
Gross Domestic Product	Gross Domestic Product (GDP) is a key economic indicator that measures the total value of all final goods and services produced within a country over a period of, typically, a year	Rajewski (1994)
Outcome (conditions)	The dependent variable to be explained by the configurations of conditions	Rihoux and Ragin, (2009)
Organisational learning	processes of creating, retaining and transferring knowledge and has implications for the performance and competitiveness of organisations"	Argote and Hora, (2017)

Chapter 1

Introduction and Research Problem

1.1 Research context

The manufacturing sector is crucial in driving economic growth, providing stability during economic downturns, and significantly contributing to the gross domestic product (GDP) of a country (Attiah, 2019; Wan et al., 2022). Szirmai (2012) explained that the characteristics of the manufacturing sector facilitate long-term economic growth and supported the notion that manufacturing drives industrialisation and can serve as the primary engine of growth. Tregenna (2009) contended that the manufacturing sector possesses 'distinct characteristics' highlighting the Kaldorian tradition in heterodox literature. The Kaldorian tradition perceives the manufacturing sector as possessing unique growth-enhancing attributes that are not present in other sectors, or at least not to the same degree (Mousa & Nassereddine, 2024). Kaldorian refers to the 'rules' proposed by Kaldor to elucidate the disparities in international growth rates. Central to this is the Kaldorian first law that posits that an accelerated growth rate in manufacturing correlates with an expedited growth rate of the overall economy, fundamentally linked to productivity rates (Marconi et al., 2016; Mousa & Nassereddine, 2024).

Manufacturing is deemed to boost exports (Sankaran et al., 2021; Sheridan, 2014), and logically, as exports are a constituent of GDP, augmenting exports inevitably leads to increased GDP, *ceteris paribus* (Sheridan, 2014). Noting that this is not always simple, Wan et al. (2022) argued that although the manufacturing sector significantly enhances economic growth in developing countries, exports and associated growth policies can contribute to de-industrialisation. This depends on factors such as the developmental stage of a country where, in some cases, it would ultimately hinder growth. Cantore et al. (2017) also argued that the manufacturing sector has a significant economic multiplier due to its strong connections to the economy's downstream and upstream output sectors. Furthermore, as the value of manufacturing stimulates economic development in African nations, policymakers are urged to increase manufacturing production (Maisiri & Van Dyk, 2021; Moyo & Jeke, 2019). The manufacturing sector also provides additional benefits, including increased employment (Mkhize, 2019; Maisiri & Van Dyk, 2021) and job

stability (Rodrik, 2018). The sustainability of manufacturing is indicated by its operations, the impact of its products and the capacity to enhance employment opportunities (Campbell & Asaleye, 2016; Cantore et al., 2017).

Critically, manufacturing also has a reduced susceptibility to economic shocks compared to other industries (Cantore et al., 2017). The South African Reserve Bank (2020) supports this view, arguing that these characteristics have led many countries, including South Africa, to prioritise manufacturing as a sector for development initiatives. As such, the manufacturing sector is extremely important to the country's growth prospects now and in years to come.

1.2 Identification of the problem and overview of research gap

Research provides critical analysis and an activity motivated by the intuition of dealing with an existing problem and the curiosity to gain new insights, answer questions, and acquire knowledge (Sakyi et al., 2020)

In this research, the context provided insights into the realities of the manufacturing sector in the economy and society. Despite its importance, the manufacturing sector has challenges (Ndung'u et al., 2022; United Nations Industrial Development Organisation (UNIDO), 2020). Central to these challenges are the diminishing size of this sector in nearly all regions and the lack of competitiveness, especially in the African region. This challenge of diminishing size is not limited to countries with already established strong manufacturing sectors. This trend is also observed in countries in the Global South with low manufacturing production levels (Hauge, 2023). In particular, African economies have experienced development and restricted diversification in recent decades, and progress in manufacturing output has, at best, stagnated or declined despite efforts to boost the sector (Nnyanzi et al., 2022). In South Africa, the manufacturing sector was responsible for about 13% of the country's gross domestic product (GDP) in 2021, which is almost half of the 24% it represented in 1990 (Figure 1.1). By 2023, this figure has remained steady at around 13% (World Bank Group, 2024a). This highlights a downward trend followed by some stability over the past few years, notwithstanding the shocks that occurred due to coronavirus (COVID-19) pandemic in 2020/ 2021. Makoni and Chikobvu (2023) highlighted that the manufacturing sector retaining then pre-COVID-19 levels indicate the sector's resilience.

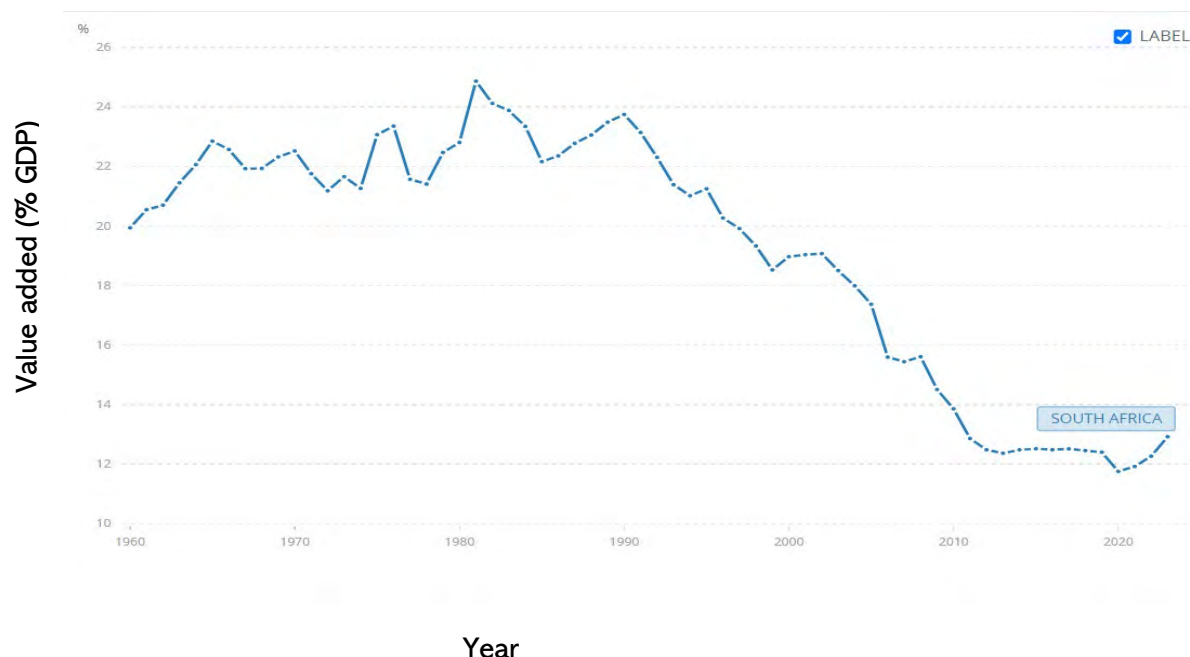


Figure 1.1: Manufacturing, value added (% of GDP) for South Africa

Source: World Bank Group (2024)

This sector is also critical for employment in the country, with 1.3 million jobs in the fourth quarter of 2023 (Statistics South Africa, 2024). Despite this, the sector has been losing jobs across all industries except, on average, the petroleum and chemical products industries (Figure 1.2) (Statistics South Africa, 2023).

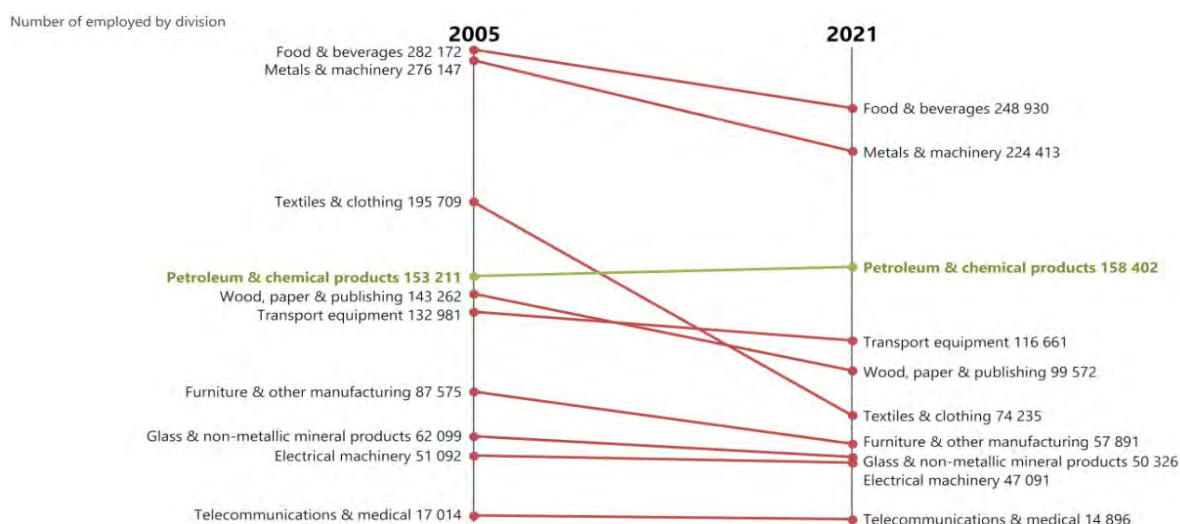


Figure 1.2: Jobs lost per industry in the South African manufacturing sector from 2005 to 2021

Source: Statistics South Africa (2023)

Furthermore, the other challenge with the manufacturing sector is that, despite its strategic importance, it is concentrated in a few areas in the country. Figure 1.3 shows

that 79% of the manufacturing jobs in 2021 were concentrated in only 10 of the 52 districts (eight metropolitan and 44 districts). Eight of these ten districts are from three South African provinces – Gauteng, Western Cape and KwaZulu-Natal.

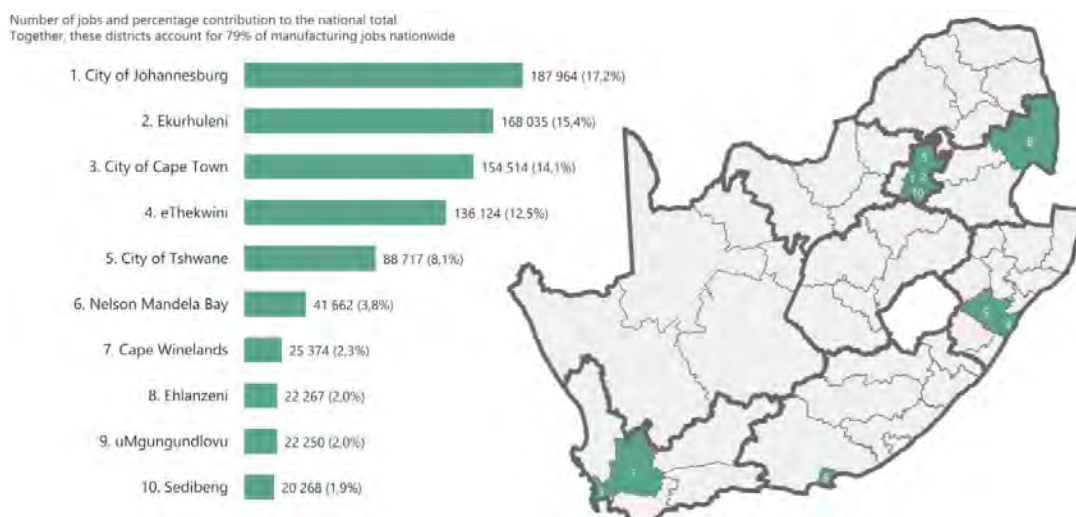


Figure 1.3: Top ten districts with the highest numbers of manufacturing jobs in South Africa

Source: Statistics South Africa (2023)

On competitiveness, the Competitive Industry Performance (CIP) Report by the United Nations Industrial Development Organisation (UNIDO), (2024) ranked South Africa 51st out of the 153 countries indexed in CIP in 2022. This is shown in Figure 1.4. This is based on manufacturing value indexes (dimension: capacity to produce and export manufactures, technological deepening and upgrading, and world impact) with a score of 0.048, lower than the world average of 0.059. Noticeably, the South African score for the share of medium and high-tech activities in the total manufacturing value-added index is 0.262, compared to the world average of 0.267, while the share of medium and high-technology activities in a total export index of 0.558 is better than the world average of 0.410.

It is also noteworthy that South Africa, although not very competitive, is ranked as one of the only four emerging industrial countries in Africa in CIP, the others being Egypt, Tunisia, and Mauritius. None of the African countries is listed in the industrialised countries category (UNIDO, 2020). This is concerning as competitiveness is closely associated with the flexibility of firms and their capability to respond to their operating environment, mainly driven by market forces, supply networks, material costs and

availability, and government regulations (Deloitte, 2013). These challenges are exacerbated by the prevailing operational uncertainties that negatively impact manufacturing firms. This results in firms and their environment having to continuously and discontinuously change, thus highlighting the challenges for effective and predicted operation (Meyer et al, 1993).

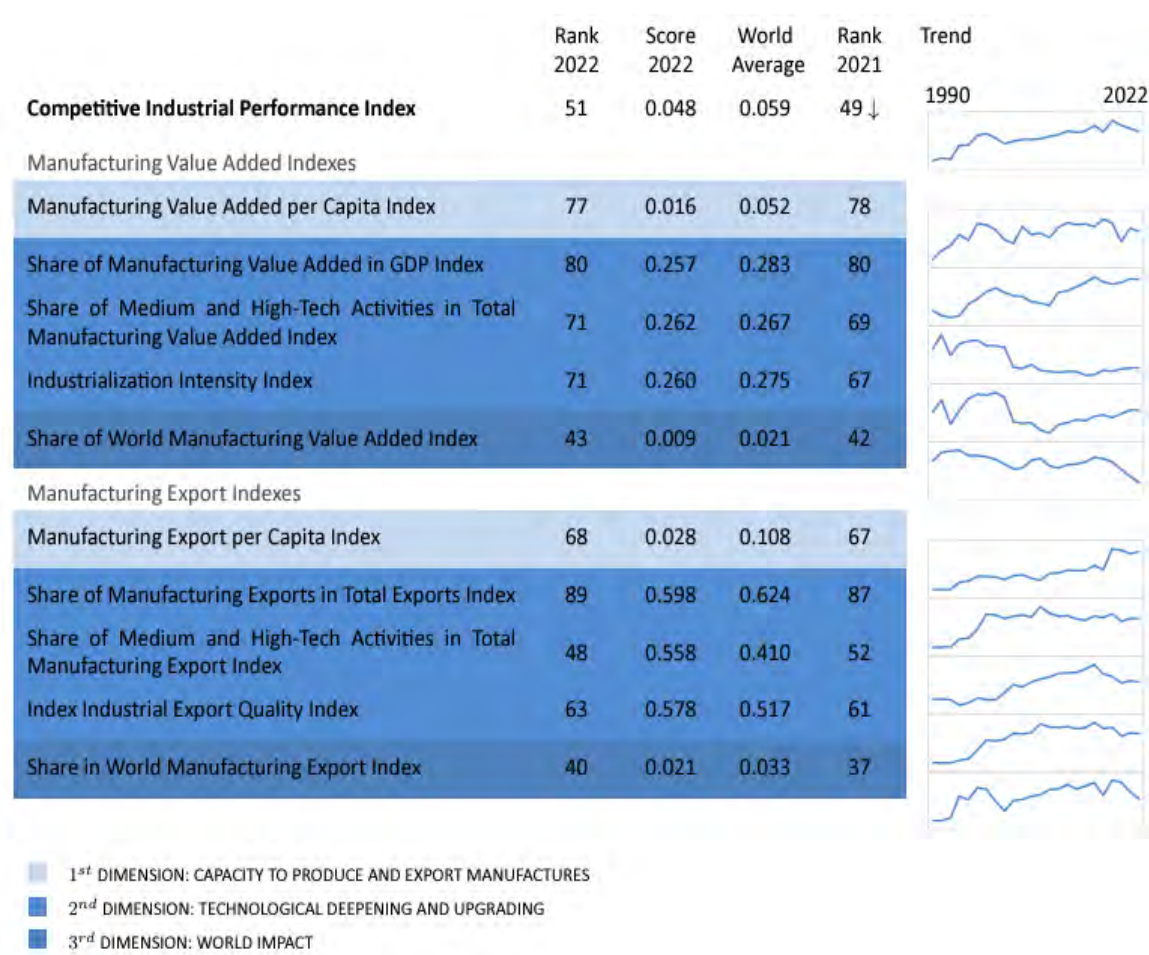


Figure 1.4: Competitive Industrial Performance Index 2024 for South Africa

Source: (UNIDO, 2024).

Thus, businesses have had to adapt to a new operating environment brought on by the increased prominence of uncertainty in operations management (Cohen et al., 2022). At this height of operational uncertainty, firms transition from a complicated style of resolving day-to-day issues to a more complex mode of operation that changes and adapts to its internal and external environment. Sammut-Bonnici, (2014) posited that the most effective way to acquire an understanding of the various interactions that operate inside a system so as to achieve particular dependent outcomes is to examine the fundamental characteristics of complex systems.

The underwhelming performance of manufacturing in Africa in recent years has cast doubt on the prospects of industrial-driven development on the continent (Ndung'u et al., 2022; Rodrik, 2018). Despite these challenges, Aryeetey (Baffour, 2022) contend that Africa can still achieve manufacturing-led industrialisation by improving Africa's global manufacturing competitiveness. This supports the earlier assertions of Signé and Johnson (2018) who argued that Africa has the potential to emerge as a prominent manufacturing hub due to certain competitive advantages it offers compared to other developing regions where industrialisation appears to have reached a plateau. Thus, there is a need, amongst others, for manufacturing firms to effectively manage complexity in their operating environment. Complexity in production systems stems from multiple sources of uncertainty that continue to present challenges resulting in operational difficulties.

Uncertainty is an intrinsic and inescapable aspect of everyday life, and to navigate uncertainty effectively, business and society must be capable of representing and reasoning with it (Halpern, 2017). More specifically, operational uncertainty is a significant global business phenomenon (Mikaelian, 2010; Sniazhko, 2019; Sniazhko, 2021) characterised by inadequate comprehension or inexact information that leads to epistemic constraints or unidentified variables (Milliken, 1987; Sniazhko, 2019). This results in many challenges in manufacturing firms regarding goods availability, high prices, labour affordability, reliability, maintenance, knowledge retention, lower sales, and changing customer preferences (Ambulkar et al., 2015; Lu & Shen, 2021). To be competitive, firms must develop items of customer-acceptable quality and deliver them at reasonable prices and with extremely predictable delivery dates. Increasing unpredictability has made it more difficult to please clients and to improve the market share of firms (Angkiriwang et al., 2014). Keeping product costs down requires efficient operations, but the capacity to respond to fluctuating or unpredictable demand in today's market may be even more important. The unpredictable nature of customer order changes, whether they be increases, decreases, cancellations, or timing shifts, requires operations management to be more flexible in a variety of ways. Firms that adeptly manage and minimise these uncertainties can transform them into opportunities for competitive advantage. These challenges test the manufacturing sector's resolve regarding survival, growth, and sustainability (Alsamhi et al., 2022; Mollah, 2019; Shepherd & Suddaby, 2017). A response is required to address such operations

management problems (Walker et al., 2015) This is particularly urgent for the manufacturing sector in South Africa and most African countries.

Identifying a research problem often leads to the discovery of a research gap, as seen in the process of posing queries and identifying new study areas based on prior research. This process is essential to expand knowledge and addressing limitations in existing studies (Ajemba & Arene, 2022). This is critical to bridge the academia-industry gap and ensure that research addresses real-world challenges, thus identifying gaps that need exploration (Elangovan, 2024). As such, the identification of the problem and research gap are intertwined to guide the research. The problem with the effective response is the dearth of theoretical and methodological research. The analysis identified three empirical and theoretical gaps as well as two methodological gaps with the synopsis provided in this section (Table 1.1), with the details in Chapter 3.

Table 1.1: Synopsis of research gaps

Type of gaps	Gaps identification
Empirical and theoretical	Operational uncertainty dimensionality, management decision tool and application
Empirical and theoretical	Leveraging capabilities of Industry 4.0 and 5.0 to manage operational uncertainty
Empirical and theoretical	Organisational learning on relationship with effective implementation of Industry 4.0 and 5.0 technologies
Methodological	Quantification index for systematic and simplified approach to assess, compare, and manage operational uncertainty complex data for decision-making
Methodological	The integrated QCA studies need attention to incorporate a method for optimising causal conditions

Source: Author

Part of that approach is understanding and managing the operational uncertainties within the manufacturing sector that threaten its competitiveness and sustainability. This requires research, as very little is known about the combined impact and management of operational uncertainty on a firm's performance. Such a response is essential to enhance theoretical development that contributes towards expertise surrounding operational management. However, improving this situation is difficult, especially with regard to developing theories that increase understanding of the management of operational

uncertainty, its mitigation, and its influence on the performance of a firm (Shepherd & Suddaby, 2017).

Sniazhko (2019) highlighted challenges regarding research on operational uncertainty resulting from inconsistency in conceptualisation and measurement, limitation to single-type uncertainty and a minimised role of decision-makers in its management (Hopfe et al., 2013; Sniazhko, 2019; Jagtap et al., 2023). This necessitates research that comprehensively identifies potential sources of uncertainty within the external environment in addition to focusing at the industrial level on individual firms (Sniazhko, 2019). In short, research to identify and effectively manage comprehensive potential sources of uncertainty (United Nations Industrial Development Organisation, 2020) requires the analysis of uncertainty as a multi-dimensional construct (Sicotte & Bourgault, 2008; Ward & Chapman, 2003).

The emergence of the fourth industrial revolution (Industry 4.0) and fifth industrial revolution (Industry 5.0) technologies are fundamentally changing the responses by firms and their approach to the increased challenge of operational uncertainty. Thus, the Industry 4.0 and 5.0 technologies have created and will continue to create an innovative way to manage operations (Dallasega et al., 2018; Koh et al., 2019; Nsakanda, 2021; Noble et al., 2022). Its effectiveness can be optimised with organisational learning. This is because organisational learning is grounded on “processes of creating, retaining and transferring knowledge and has implications for the performance and competitiveness of organisations” (Argote & Hora, 2017, p.579). The capabilities of the technologies of Industry 4.0 and 5.0 are anticipated to foster flexibility and adaptation, enabling a dual role of reducing operational uncertainty and coping with its impacts (Naseem & Yang, 2021; Noble et al., 2022; Santhi & Muthuswamy, 2023). As a result, efforts are ongoing and need enhancement to guarantee that businesses can capitalise on the benefits of this transformation associated with Industry 4.0 and 5.0 technologies while managing inherent operational difficulties.

1.3 Goals of the research

Operating environment transformations and advancements observed in recent decades significantly impact the business world (Naughton et al., 2020). This also holds true for manufacturing, with this important sector facing challenges mainly influenced by the environment associated with high levels of operational uncertainty. This study aims to

develop an approach for managing operational uncertainty with fourth- and fifth-industrial revolution technologies. In developing an operational configurational theoretical and methodological perspective for sustained firms' performance during operational uncertainty, this investigation used the following objectives:

Objective 1: To develop a comprehensive understanding of operational uncertainty in manufacturing.

Objective 2: To review and validate the capabilities of fourth and fifth industrial revolution technologies in manufacturing operations and linkage to organisational learning.

Objective 3: To formulate and analyse sustainable performance configurations (outcomes condition) with causal conditions from operational uncertainty, Industry 4.0 and 5.0 technologies and organisational learning.

1.4 Significance of research for the manufacturing sector

Wernerfelt and Karnani (1987) posited that firms have a choice to act and confront and mitigate the challenges related to the prevailing uncertainties or to wait, hoping that they will resolve themselves with any change in the operating environment. This happens while competition is challenging the firm's existence. This research proposes a need to act to confront and mitigate the operational uncertainty challenges, which is significant for manufacturing firms in South Africa. Although South Africa is the primary research setting, the study has implications that can extend beyond its primary setting, affecting broader contexts, informing practice, and further research in related settings. Such areas are similar to developing countries such as the BRICS+ and other African countries.

1.4.1 Relevance of the study for manufacturing in BRICS+

Brazil, Russia, India, China, and South Africa, commonly known as BRICS, have collaborated to create a massive emerging market economy (Kutu & Ngalawa, 2016). The BRICS countries' collective contribution to the world's total production rose from 8% to 19% between 2000 and 2011. In addition, the BRICS formed BRICS+ in January 2024 with the addition of Egypt, Ethiopia, Iran and the United Arab Emirates to the original group of five countries.

The BRIC countries were hit by the global financial crisis of 2008 to varying degrees (Hess et al., 2019). Despite this, these country's economy recovered quickly and by 2010 even exceeded its rate prior to the crisis. In general, the economies of the BRIC nations performed better than those of industrialised Western nations (Banerjee & Vashisth, 2010), particularly those that had long controlled the landscape of international financial lending. The disparate economic performance of the different BRICS countries has a potential to pose a significant obstacle to the coherence of the bloc's economic and strategic interests. Of particular note here is China's exceptional performance in the industrial sector, rapid income development, rapid technological advancement, and its capacity to fulfil its financial obligations (Chatterjee & Naka, 2022). Compared to the development of other countries, China's manufacturing sector has been responsible for a comparatively greater significant portion of the country's overall growth (World Bank Group, 2024). There are factors that contribute to China's success: compared to Brazil, the Russian Federation, and South Africa. China has been in a development stage over the past two decades, economically and socially (Dunford, 2024) as well as technologically (Xu et al., 2017). Furthermore, China has a dominant manufacturing sector and huge advances in technological capabilities (Asif et al., 2024); especially in artificial intelligence (Liu et al., 2022; Wang et al., 2023).

China has had a comparative advantage in the manufacturing sector for the past two to three decades, while Brazil, the Russian Federation and South Africa have already passed the period of development associated with rapid industrialisation. This advantage has allowed China to develop faster than its manufacturing sector competitors. The difference between actual and projected levels of development in China was the largest positive gap of any of the BRICS countries (Haraguchi et al., 2015). The Trade in Value Added Database (TIVA) measures the global value chain participation and position index of the manufacturing industry in BRICS countries. It then compares these results with those obtained for developed countries to determine the extent to which manufacturing industries in BRICS countries are embedded in the global value chain. At a technological level, it is noteworthy that India also to improve and integrate Industry 4.0 and 5.0 into manufacturing, improving efficiency and competitiveness (Gupta et al., 2021). The BRICS countries' external value-added ratio in the final output, as well as the development of their internal cooperation, are measured by the World Input-Output Database (WIOD) maintained by the European Union (EU). Overall, the following can be conclusions: (1)

Although the external value added by member countries in the manufacturing industry is low, the internal cooperation between the BRICS countries is closer than ever; (2) Other BRICS countries, with the exception of Brazil, have a lower position in the global value chain (Li et al., 2024).

The BRICS nations, through the BRICS Business Council, developed nine working groups which included manufacturing (BRICS Business Council, 2023). The main strategic focus in trade and investment, along with the manufacturing working group, is to facilitate trade in manufacturing among the five countries and also to encourage co-operation on projects where there is potential for collaboration or complementarity. The present study is relevant in that context as it creates learning that can be shared and promote collaboration in recognising and managing operational uncertainty by using the capabilities of Industry 4.0 and 5.0 technologies in manufacturing in the BRICS+ countries. This is important as Industry 4.0 and 5.0 technologies are transforming manufacturing in China (Li et al., 2024) and India (Wagire & Kulkarni, 2024) by integrating advanced digital technologies, thereby improving operational performance.

1.4.2 Relevance of the study to South Africa and other African countries

The present study is also relevant to other African countries, and its implications can create a base for further developments and improvements in manufacturing in Africa. By 2030, it is expected that business-to-business (B2B) manufacturing spending in Africa will total \$666.3 billion (R12 trillion), an increase of \$201.28 billion (R3.62 trillion) from 2015 (Signé & Johnson, 2018). This augurs well for the future of African manufacturing sector. Nguimkeu and Zeufack, (2024) posit that manufacturing remains a viable and reliable path towards structural transformation in Sub-Saharan Africa. This despite the manufacturing had experienced a series of external shocks, including rising oil prices, falling commodity prices, rising real interest rates, shrinking public funds, and the limitations of domestic markets (Signé & Johnson, 2018). Although there have been encouraging signs of recovery, Africa's manufacturing sector remains well behind that of other areas due to a combination of issues that make it less competitive (UNIDO, 2024). Reasons for these poor performance indicators include the high cost of doing business, an uncertain political and regulatory climate, a lack of clear long-term policy objectives, inadequate infrastructure, and an over-reliance on natural resources (Ndung'u et al.,

2022). Borat et al. (2017) posited that in the sub-Saharan African region, productive structure is characterised by lower levels of economic complexity. In contrast, the production organisation of East and South Asia is interconnected and complex. These findings show that although Asia's manufacturing industry is huge and is sufficiently diverse so as to generate a wide range of job prospects, while Africa's manufacturing sector is small and somewhat stagnant. Despite this, the data as a whole show that African manufacturing exporters are becoming increasingly integrated into global production networks. However, its role is shifting from downstream final product providers to upstream intermediate input suppliers (UNIDO, 2020).

The potential practical contribution of the present study is to improve development and foresight for the management of manufacturing industries in developing economies such as South Africa and other African countries. This is important in the context of the proposed development of economic zones and African Continental Free Trade Area (AfCFTA) The construction of economic zones aimed to compensate for the sluggish infrastructure and are expected to help foster the growth of internationally competitive businesses on the continent (Storonyanska & Patytska, 2022) This will be useful as emerging economies are expected to be fully integrated into a digitally revolutionised economy by the year 2030. These emerging economies are expected to feature technological innovation in all industries for its resources' control, ownership, and sovereignty (Nyagadza et al., 2022). Furthermore, the African Continental Free Trade Area (AfCFTA) provides South African and other African countries' industries with a new avenue for expanding trade with the rest of the continent. (Oluwatosin et al., 2024).

1.5 Theoretical and methodological significance in operations management

1.5.1 The theoretical significance of the research

To deal with these prevailing forms of uncertainty that affect a firm's performance (Silva & Ferreira, 2017) businesses are coming up with new ways of tackling old operational challenges, which has opened up space for the testing and refining of existing operations management theories as well as the creation of new ones (Alfaro-Tanco et al., 2021; Dresch et al., 2019; While developing or refining theories is a necessary step in expanding management knowledge, doing so is a very challenging endeavour. Most previous research in operations management concentrated on theory testing rather than

theory building (Walker et al., 2015). Finding connections between theory and practice is essential, and the underlying theory helps this process as it enhances the research's level of abstraction and potential impact.

The present study is significant for operations management and operations research. Operations management (OM) encompasses intricate interactions between individuals, technological systems, and organisational and physical procedures, many of which undergo transformations over time (Peinado et al., 2018; Dhiaf et al., 2021). Thus, OM has a wide range of meaningful, relevant, and consequential aspects to address (Walker et al., 2015). These fall within the areas of supply chain management (Abbasi & Varga, 2022; Alexander et al., 2022), product and service design (Joly et al., 2019; Jiang et al., 2021), lean management (Santos Bento & Tontini, 2018; Ferreira & Saurin, 2019), quality management (Fundin et al., 2020; Gremyr et al., 2021), and decision support (Baldwin et al., 2010), among others.

Operations management has encountered new challenges resulting from global competitiveness, co-development, co-creation of products, innovation, technology integration, global supply networks, sustainability and corporate social responsibility (Sadeghi Moghadam et al., 2021). This requires a more holistic integration of other management disciplines and expanding enterprise-wide responsibilities within management. This is because OM is characterised by its dynamic nature, as it constantly witnesses the emergence of new practices within a complex and uncertain environment. The presence of uncertainty significantly influences investment decisions made by firms, subsequently affecting the manufacturing process and ultimately leading to disruptions in exports and the trade balance (Dagar & Malik, 2023). In addition, firms have found themselves confronted with the challenging circumstance of a decline in overall demand, initially resulting from a supply shock and subsequently exacerbated by job losses (Bendoly et al., 2022; Guru et al., 2023).

Best practices in operations management have matured, and research on these practices has shifted focus from explaining their value to the contextual conditions under which they are effective in firms (Sousa & Voss, 2008). Despite this, the field of research in operations management presents distinct challenges, namely a dearth of theoretical frameworks, complexity in its subject matter, and a deficiency in robustly established definitions and metrics (Sadeghi Moghadam et al., 2021). Numerous researchers have

made significant and valuable contributions to advancing theory in operations management (Schmenner & Swink, 1998; Narasimhan, 2014; Walker et al., 2015) and more recently, there was an increase in theory-driven empirical research (Roth & Rosenzweig, 2020).

Several academics have investigated operational phenomena by applying management and organisational science concepts in response to this development and the root dependency that generally characterises research. As such, it is important to reflect on theories since they impact how research analyses and addresses operations management problems. This is essential in enhancing expertise in OM while considering theoretical developments. This allows the research to reflect on the collective literature to identify trends and gaps. Not only is OM crucial to getting things done, but it is also essential for promoting discussion about what topics currently or potentially belong to the body of knowledge surrounding operations management and how that information is applicable in practice. There is a new opportunity to think about how OM may help business leaders now and in the future (Peinado et al., 2018). Within the realm of OM constructs, operational uncertainty is of great topical importance, especially as a myriad of global challenges are changing the face of manufacturing. This operations management study is completed by using and applying advanced analytical methods to improve decision-making within the complex operating environment so as to optimise operations.

The underpinning theory must demonstrate the existence of the research topic, justify the research as one that adds to the existing body of knowledge, or validate the proposed study's methodologies and approaches. The analysis in the present study identified chaos theory (Houry, 2012; Namaki, 2018; Mbengue et al., 2018), systems theory (Mele et al., 2010) complexity theory (Sammot-Bonnici, 2014) contingency theory (Donaldson, 2001; Sambamurthy & Zmud, 1999) and configurations theory (Fiss et al., 2013; Pla-Barber et al., 2020) as the foremost theories that can potential underpin the studies of operational uncertainty on a firm's performance.

1.5.2 Methodological significance of the research

The methodological significance of this research was its expected contribution to the advancement of research practices by developing a new methodological framework, improving existing methods, and its interdisciplinary use. It emphasises the appropriateness of the selected methods for addressing the research issues and

elucidates their contribution to the field by introducing new methodological paths. The methods utilised in this research signify a notable progression in examining operational uncertainty in manufacturing. This research tackles a significant gap in existing approaches by merging predictive analytics with decision-making models. The novel integration assists with an adaptive framework for comprehending how firms can manage operational uncertainty in manufacturing. This method improves prediction accuracy and offers a reproducible approach that is applicable to other industries experiencing similar challenges, such as the mining, energy, and transport sectors.

The methodological contribution is propelled by the need to continuously develop research methods and data analysis tools and techniques for analysing and developing solutions for complex problems. Most common methods and models are robust; the analysis is not easily holistic, as it is a collection of data prepared from an initial, different purpose, and the variables are not holistic in design. As such, research has turned to models capable of analysing complex systems characterised by uncertainty and nonlinearity (Kumar et al., 2022). Roig-Tierno et al., 2017) explained that adopted sophisticated methodologies and algorithms are useful for establishing and quantifying causal relationships between variables and their complex interactions.

The non-linear analysis approach is highly effective in capturing the conjunctural forms of causation that underlie theories of complementarity. Complementarities arise from certain arrangements in which causal elements converge to generate a result. This is contrary to traditional statistical methods that quantify the overall impact of individual variables while keeping other factors unchanged, known as the "net effect" (Witt & Jackson, 2016)

1.6 Research scope and delimitations

The research scope and delimitations serve to establish the larger parameters and boundaries of the investigation. The scope delineates the research's specific parameters, including the investigation's breadth, while the delimitations highlight the specific characteristics and variables that are intentionally excluded from the study. This enables readers to comprehend the research emphasis and anticipate the type of content encountered in the research. These are based on the constructs of the study and the methodological scope.

1.6.1 Scope of operational uncertainty

The study focused on multiple facets that assist in building configurations of sustainable performance. The research considered the multi-dimensional construct of operational uncertainty investigated at the operational environment, industry and firm level. The research focused on nine identified constructs, that are: growing geopolitical tension, policy and regulatory uncertainty, high cost of living-driven consumer behavioural change, pandemic turbulence, lack of energy stability and security, operational uncertainty from generational work behaviour and ethics, availability of skills for future work, entrenchment power of large firms, low process capability and high variations. These are synthesised in Chapter 3. Other potential operational uncertainties that were not included can complement or supplement some of the dimensions based on a particular research context and focus.

1.6.2 Scope of Industry 4.0 and 5.0 technologies in manufacturing

Bibliometric analysis helped to identify the technologies most widely used in Industry 4.0 and 5.0 in the manufacturing sector. This was done using Scopus and Web of Science (WoS) databases, which offer extensive and comprehensive data sources for various uses (Zhu & Liu, 2020). The conceptual structure was assessed using a network approach with a co-occurrence network and thematic map. The study identified co-occurrences among the keywords assigned by Scopus and WoS to each publication within the dataset. Consequently, the Louvain cluster technique was employed to establish connections between the top 50 most developed keywords (Boyack & Klavans, 2010).

Figure 1.5 highlights the conceptual structure of the dataset - co-occurrence network on Industry 4.0 and 5.0 technologies and its capabilities in manufacturing.¹

¹ The R-package utilising RStudio and Biblioshiny including combining the multiple WoS files and the WoS combined file with Scopus databases.

For WoS the search string was: fourth industrial revolution technologies (All Fields) or fifth industrial revolution technologies (All Fields) and manufacturing (Abstract) and capabilities (Abstract)

For Scopus: (ALL (fourth OR fifth AND industrial AND revolution AND technologies) AND TITLE-ABS-KEY (manufacturing) AND TITLE-ABS-KEY (capabilities)). These databases were combined: Combined_new1 <- mergeDbSources(web_data, scopus_data, remove.duplicated = T).

In Figure 1.5, the first cluster (purple) is Industry 4.0, focusing on the technologies and their capabilities. The most dominantly highlighted were the Internet of Things (IoT), artificial intelligence (AI), Robotics, Additive manufacturing (3D printing), and big data (more evident in cluster 2). Others at very low frequency include blockchain, augmented and virtual reality, quantum computing, and broad cyber-physical systems. This cluster also shows a high network of these Industry 4.0 technologies with capabilities such as embedded systems, production systems, flow control, data analytics, digital storage and automation, industrial research, education, and industrial research. Industry 5.0 was negligible, as was the technology within manufacturing. Cluster 2 (green) links Industry 4.0 within the manufacturing firm's key competencies, including sustainability or sustainability as development, supply chain management, lean production within big data, and cyber-physical systems. Cluster 3 (red) mainly focuses on the framework, model, impact, and capabilities, simply put, the vehicles for execution, while Cluster 4 (blue) highlights the dynamic capabilities, innovation, and performance. The last cluster (orange) delves into integration and competitive advantage, which is the ultimate goal for a manufacturing firm. Based on these findings, the study investigated eight Industry 4.0 and 5.0 technologies: Internet of Things (IoT), artificial intelligence (AI), big data analytics, (BDA) robotics and advanced robotics (ARB), additive manufacturing (3D printing) (ADM), blockchain (BCC), augmented and virtual reality (ARVR), and quantum computing (QCP). The scope and delimitations of a study were crucial components of this research, as they provided context and defined the specific focus and restrictions of the research.

The study focused on the manufacturing sector inclusive of the different industries. However, no in-depth analysis of the individual industries is advanced in this study except baseline of level of use of Industry 4.0 and 5.0 technologies. Industries were analysed to aggregated the sector. Lastly, the study focused on developing countries, specifically the manufacturing sector of South Africa, although it is contextualised to be applicable in BRICS+ countries and other African countries. Although intersecting with developing countries, developed countries were not the focus of this study

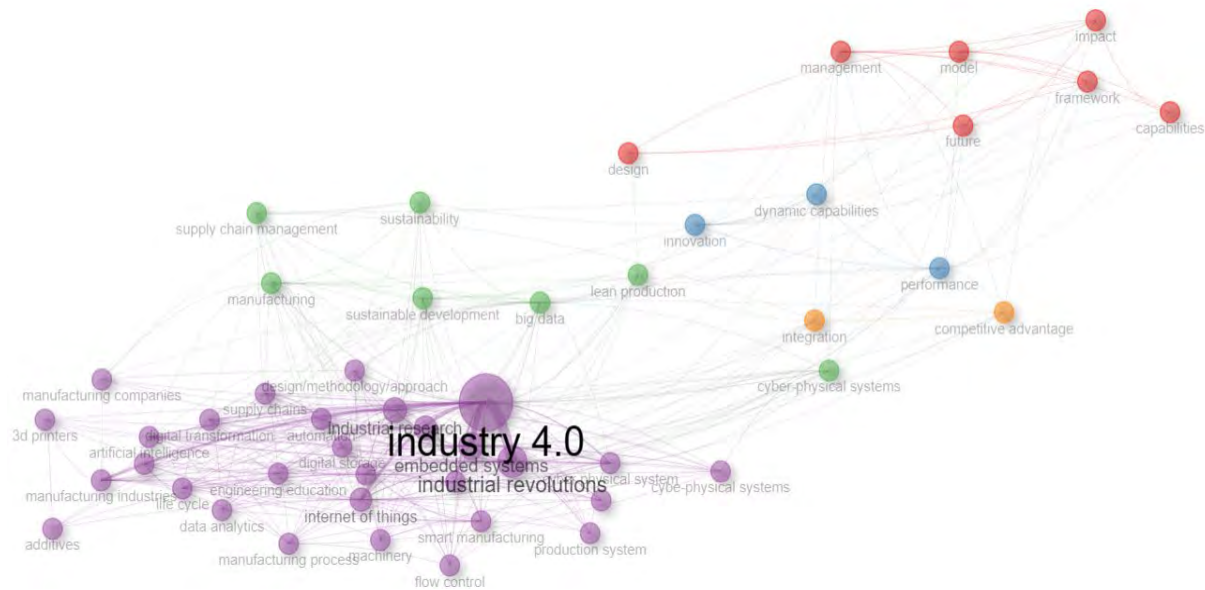


Figure 1.5: The conceptual structure of the dataset – co-occurrence network

Source: Author

1.7 Assumptions of the research

The challenge of reducing a complex system to essential interactions complicates the creation of models for complex systems. In many instances, data are insufficient to specify all parts of a system or are improper for interaction definition; hence, model developers must incorporate assumptions into each system representation (Messina et al., 2008).

The literature supports the critical assumption that the world is increasingly complex and solutions are not linear (Verissimo et al., 2024). This also holds true for the manufacturing sector. Saptioratri Budiono et al. (2021) argued that the manufacturing sector cannot be separated from market uncertainty, dynamic environmental conditions, competitiveness, and changing customer needs and requirements. Complexity in manufacturing systems remains challenging, leading to operational issues and increased production costs (Alkan et al., 2018; Vidal et al., 2023). The other assumption is that complexity is due to multi-dimensional issues that affect a firm's strategic position and efficiency in operation (Vogel & Lasch, 2016). As such, the resolution of complex problems has become increasingly pertinent across several sectors, necessitating the capacity to recognise and address multi-dimensional, ill-defined issues that demand consideration of diverse information and perspectives. Furthermore, management of operational uncertainty is possible as

there is an availability and accessibility of technology in manufacturing firms. This assumption is plausible as the manufacturing sector has comparative medium and high technology activities in the total manufacturing value added index with the world average and better than the world average for the total export index (UNIDO, 2024).

1.8 Preface of the report

Figure 1.6 provides a visual map showing the different areas included in the present research study. This comprises the grounding and operationalising theories, the emergent core tenets, empirical analysis using multi-methods falsifying and utility of the theoretical perspective, and the development of the emergent neo-configurational perspective.

The report comprises ten chapters for managing operational uncertainty in manufacturing with Industry 4.0 and 5.0. Chapter 1 introduces the research by providing the background and context of the study, identifying the problem, and then the research goals and objectives. This chapter also identifies the scientific significance of theory, methodology, and practice before closing by presenting the research's delimitations, scope, and assumptions. Chapter 2 focuses on the synthesis and selection of the grounding and operationalising theories of the study. The chapter links the selected theories, complexity and configurational, and compares their core tenets.

In Chapter 3, the focus is to review the literature and also develop the configurations of the research, which includes causal conditions – operational uncertainty, Industry 4.0 and 5.0 technologies, and organisational learning and outcome–sustained performance. This chapter also presents the research gap, which assists in advancing the emergent core tenets. The core tenets were used to develop research propositions.

Chapter 4 advances the use of qualitative comparative analysis (QCA), an effective method for the study and discusses the theoretical and methodological positions of QCA. This chapter also provides the methodological gap of the study that is based on QCA. Chapter 5 presents the methodology that explains the 'how' part of the study and discusses how the research investigation took place. This is done by highlighting the research design and justifying the selected choice, followed by population and sample. After identifying a population and a sample, the population, unit of analysis, sample size, and sampling strategy are presented. The methods of the study are as follows: research

instruments, data gathering approach, data analysis, credibility, and rigour of research to ensure quality and ethical considerations. The chapter closes by explaining the technical and administrative weaknesses, which are methodological limitations of research.

Chapters 6 to 8 present the research results from the manufacturing firm survey and expert assessment based on the objectives. Chapter 6 develops a comprehensive understanding of operational uncertainty in manufacturing. This chapter identifies operational uncertainty dimensions, confirms multidimensionality, and understands the causal and effect dimensions and their impact on the operations determinants in manufacturing. Chapter 7 describes the review and identifies Industry 4.0 and 5.0 technologies in use in the sectors and their capabilities in managing operational uncertainty. Chapter 8 develops the configurations for sustained performance with fuzzy-set qualitative comparative analysis (fsQCA). Chapter 9 discusses the study results and develops a framework of operational configurational theoretical perspective for sustained performance of firms during operational uncertainty - a modified neo-configurational perspective. The research is closed in Chapter 10 with a conclusion and research contributions. This last chapter also provides the study's limitations, which helps contextualise the findings, implications for the sector and policymakers and the proposed direction for future research.

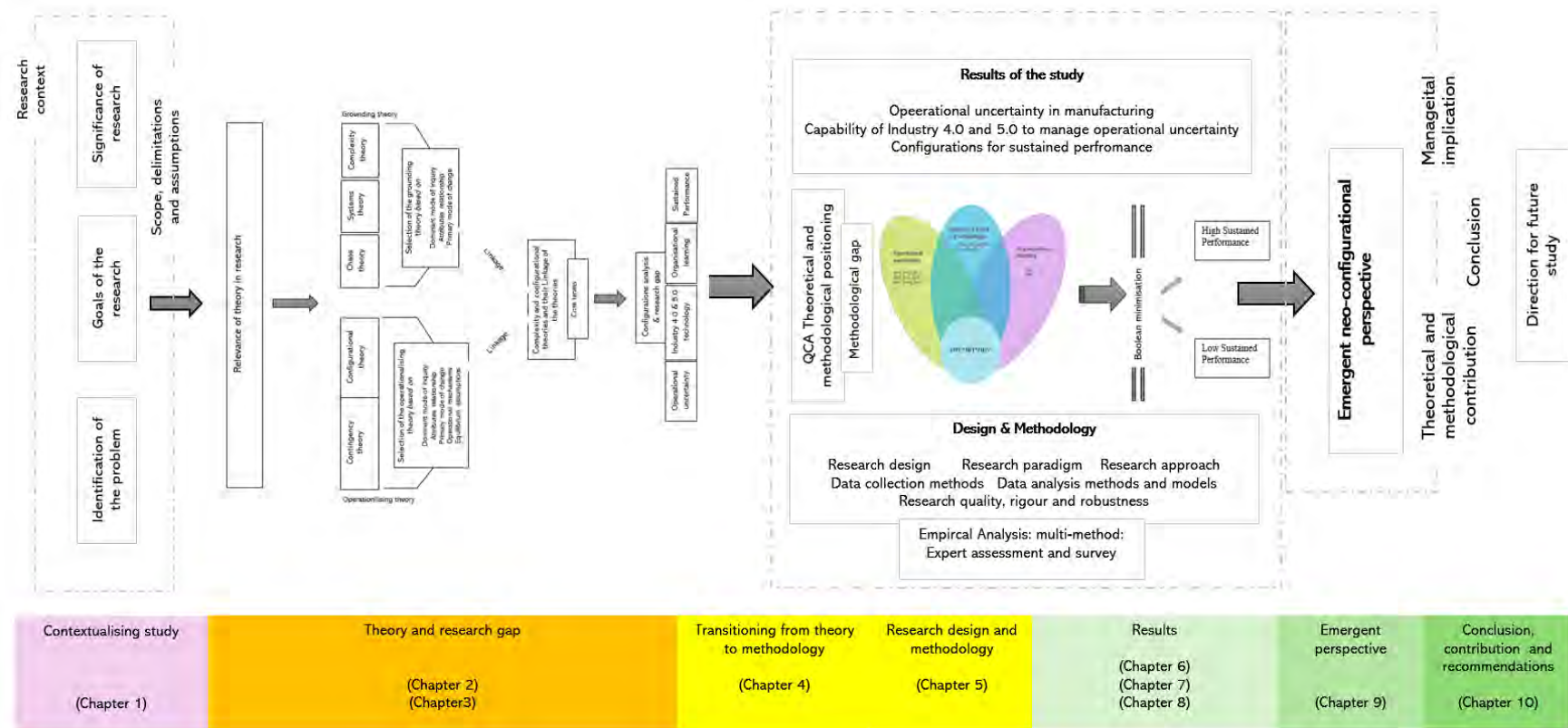


Figure 1.6: Mapping of the research study

Source: Author

Chapter 2

Theories of the Study – Grounding and Operationalising

2.1 Introduction

Theory is critical for interpreting or comprehending research and to be able to contribute to the development of new knowledge (Eriksson-Zetterquist et al., 2021). It provides "currency" for scholarly research (Corley & Gioia, 2011; Fawcett, 1978; Post et al., 2020) as it guides a comprehensive analysis of a phenomenon, elucidating the underlying mechanisms and causal factors that contribute to its occurrence. This chapter discusses various theories and relevant selected theories for grounding and operationalising the study. The chapter starts by discussing the relevance of the theory to research. It then provides an overview and selection of the grounding theory and the operationalising theory and the interlinkages between these theories and their core tenets. These are indicated in Figure 2.1. The configurations of the study – causal conditions (operational uncertainty, Industry 4.0 and organisational learning) and outcome (sustained performance) are discussed in Chapter 3.

The grounding theory underpins the entire study and provides a broad conceptual foundation, helping to define the research problem within a larger context. It offers a lens through which research ensures that it is coherent and connected to existing knowledge. It also helps in understanding the phenomenon being studied and to situate the research within a broader academic or practical context. The operationalising theory is critical as it entails converting its abstract concepts into quantifiable, observable, and verifiable constructs or cases (causal conditions and outcomes) that are applicable to research. It also specifies the methods by which the theoretical constructs are observed or quantified within the framework of the study. The chapter concludes by linking this research's grounding and operationalising theories

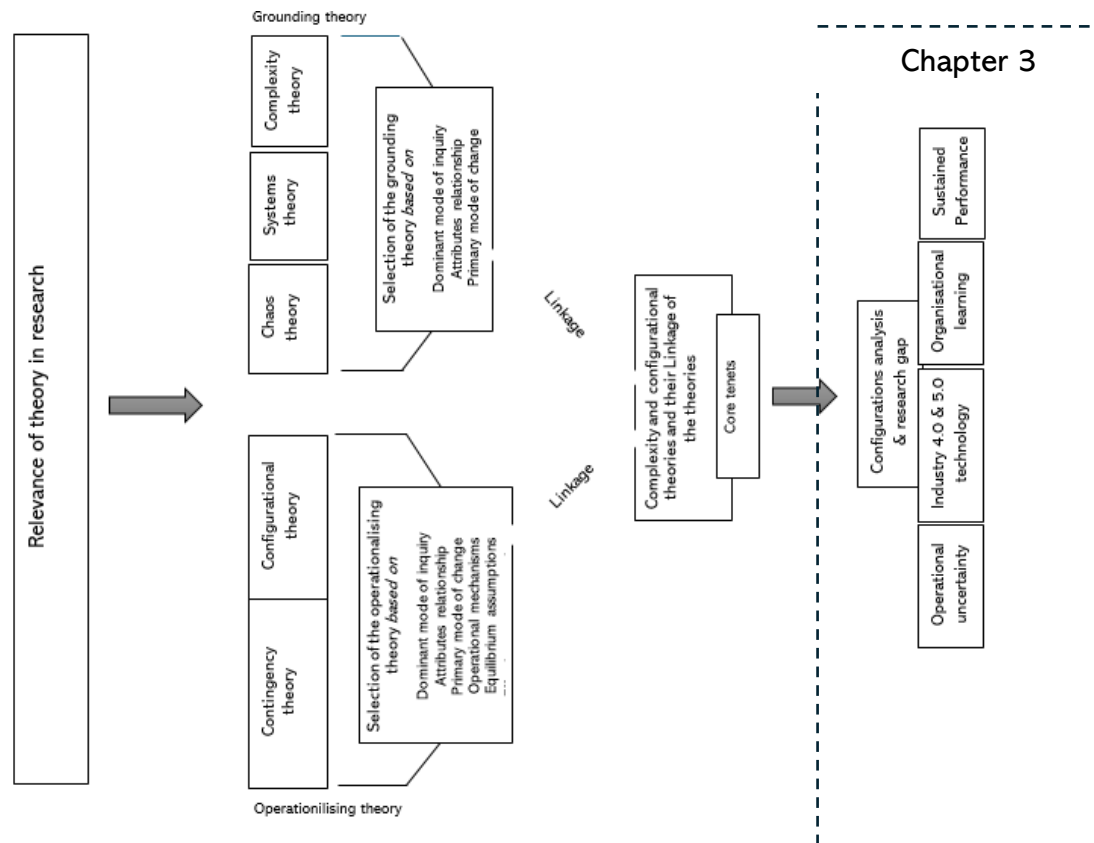


Figure 2.1: Grounding and operationalising theory selection approach

Source: Author

2.2 Relevance of theory in research study

Theory serves as a fundamental pillar regardless of whether the research uses quantitative or qualitative methods. The use of theory in research varies, yet in both types of research, the incorporation of theory is considered an essential component of research (Fried, 2020; Rengasamy, 2016). Without theory, it is hard to interpret empirical evidence meaningfully and to discern between successful and unsuccessful outcomes (Diaz Andrade et al., 2023; Fried, 2020). Also, without theory, empirical inquiry becomes nothing more than "data dredging".

The development of theories helps to distinguish science from common sense. Despite variations in the level of detail and specificity, extant definitions of "theory" share a common understanding that it is a body of conceptual knowledge that seeks to elucidate phenomena (Van Assche et al., 2023). The bodies of knowledge that compose theories originate from contributions from various disciplines, so new theories are constantly being developed and utilised in many contexts. Research relies heavily on theory-building since it lays the groundwork for analysis and promotes productive growth in the relevant

discipline (Gay & Weaver, 2011). It is also essential for practically solving real-world problems, so the research must settle on a suitable theory that is applicable and underpins the study (Grant & Osanloo, 2014). There are three relationship types in theory building: descriptive, explanation, and prediction. The focus of a description is on developing an image of a critical phenomenon, while an explanation focuses on how and why the relationship exists or takes place between the phenomena in a particular form, with all being grounded in theory. On the other hand, a prediction goes beyond the explanation approach as it provides the basis for why particular results emerge when there is a specific set of conditions (Ketchen et al., 2022).

Studies can engage in theory testing to better understand a topic, which involves applying previously established theories in novel ways or contexts (Colquitt & Zapata-Phelan, 2007). Finding commonalities across disparate fields is crucial to theory-building since doing so raises the level of abstraction and potential impact of the research. Theories in research serve various functions depending on their application (Zhang, 2010). In the present research, they served two important functions by providing the grounding of the study and operationalisation of the research. Simply put, grounding theory provides the "why", the broad explanation of why the study is important and how it fits into the existing body of knowledge, while operationalising theory provides the "how", the theory that operationalises the research as it translates the abstract concepts of the grounding theory into measurable variables or constructs. It helps to define and measure the key elements of the research. The practical way of measuring, observing, and analysing the key components of the study. This ensures that the research is both theoretically sound and practically feasible.

2.3 Selection of relevant grounding theory

This study's initial analysis identified chaos theory (Houry, 2012; Mbengue et al., 2018; Namaki, 2018; Thiétart & Forgues, 1995), systems theory (Mele et al., 2010) and complexity theory (Sammot-Bonnici, 2014), as the foremost theories that needed to be analysed to select the most optimum grounding theory for this research.

2.3.1 Overview of chaos theory

Chaos theory gained relevance in social, business, and economic sciences in the past few decades (Houry, 2012; Mbengue et al., 2018; Namaki, 2018). This theory is founded on

two basic tenets; the first is that systems, regardless of their degree of complexity, are governed by an underlying overarching equation or principle, making it theoretically deterministic despite its instability and the presence of a high number of contributing factor (Biswas et al., 2018; Fernández-Díaz, 2023). The second major component is the dynamic system's extreme sensitivity to beginning conditions, in which a minute change in the initial conditions can result in catastrophic and unforeseen effects (Biswas et al., 2018).

Thiétart and Forgues (1995) provided several characteristics of chaos theory, and these included sensitivity to initial circumstances, discreteness of change, attraction to specific configurations, structural invariance at various scales, and irreversibility. Su (2021) supported some of these characteristics, such as sensitivity to initial values, arguing that subtle changes will affect the final shape and state of the entire structure. Chaos theory is not only one of the most active branches of the dynamical system, but also one of the most important topics of the nonlinear scientific field (Namaki, 2018). When a firm is in the chaotic domain, tiny adjustments might have large and unpredictable long-term effects, with unusual attractors emerge from the chaos and are incorporated into the firm's arrangements (F. Su, 2021). Furthermore, similar patterns must exist at various scales; as such, during the lifetime of a single firm or between two firms, comparable activities would not lead to the same outcome (Thiétart & Forgues, 1995; Su, 2021).

Given the constantly changing and intrinsically unpredictable business settings in which firms operate today, all strategic managers, regardless of the industry in which they operate, should give chaos theory serious and meaningful consideration (Sullivan & Daniels, 2008). In a chaotic environment, organisations are prone to display chaotic system characteristics (Mbengue et al., 2018). Mathematicians and scientists contributed to the development of chaos theory, which has numerous scientific applications (Biswas et al., 2018). Gregersen and Sailer (1993) contended that the traditional aims of the social sciences—the "prediction" and "control" of system behaviour—are often, if not always, impossible to achieve. When the underlying systems are exceedingly simple and totally deterministic, chaos theory demonstrates that essentially identical creatures embedded in identical settings can exhibit drastically divergent behaviour. In addition, the universality of chaos theory's supporting ideas means that they can be applied to a wide variety of social science issues involving individuals, communities, and even nations.

In management, various decision-making models are devised based on the decision-making process in specific, controlled situations and stable surroundings.

In chaos theory, the disorder has overrun all scientific fields, and decision-making models are no exception. According to the conventional view of management, decision-making is a predictable process, and failure in decision-making results from a lack of knowledge or limitations in prediction techniques and effort (Namaki, 2018). In contrast, chaos theory assumes that decision-making is unpredictable and that attempts to foresee the future are futile. At the very least, it believes that accurately and confidently predicting the future is difficult. In chaos theory, it is thought that correct and complete information cannot be obtained and that events are constantly unpredictable and have no connection to the past (Levy, 2007; Namaki, 2018). Positive feedback in chaos theory is applied to reinforce deviations from equilibrium, thereby fostering creativity within organisational settings. The chaos approach is a strategy utilised to modify cognitive processes, conduct, managerial methodologies, and structural frameworks to facilitate efficient operation in dynamic and intricate situations (Uys, 2002).

Several managerial implications can be drawn from seeing industries as chaotic systems. Chaotic systems make accurate long-term predictions nearly impossible, and sudden and radical shifts necessitate organisational agility and responsiveness to thrive. However, chaotic systems display some order, allowing for short-term prediction and the identification of underlying patterns. Chaos theory highlights guidelines and decision rules for dealing with complexity and the pursuit of less evident and indirect approaches to achieving goals. Biswas et al. (2018) posited that a significant shortcoming of chaos theory is its inability to foresee the future with any degree of accuracy. It is useful for predicting patterns in the near future, but as time passes, more variables influence the actuality, and it becomes less accurate, and it becomes more difficult to forecast what will occur. The view regarding this theory's inability to predict extended periods as it becomes less accurate is also supported by (Goulielmos, 2019).

2.3.2 Overview of systems theory

Systems theory, often known as broad systems theory or systemics, leads to system study. This theory is based on a set of concepts from several closely connected intellectual areas that study system nature and properties (Straussfogel & von Schilling, 2009). A system is a cohesive collection of natural or artificial mutually dependent parts such as

for example in manufacturing the production and maintenance (Halloui et al., 2022). Von Bertalanffy (1968) conceptualised a system as 'components in a stable relationship.' A system is a structured entity composed of interconnected and interdependent components (Drack & Pouvreau, 2015) and is characterised by its temporal and spatial limits, influenced by its environment, and defined by its purpose, nature, and structural performance. A system exhibits emergent behaviour and synergy, rendering it greater than the mere sum of its components. Modifying one component of the system typically affects other components and the system as a whole, influencing anticipated behavioural characteristics. The objective of systems theory is to comprehensively identify a system's limitations, conditions, dynamics, and foundational principles that can be applied and understood across all levels of nesting and in every domain. Turner and Baker (2019) highlighted that recent work has questioned the relevance of systems theory to contemporary research and practical needs, with a suggestion that social sciences research abandon reductionist frameworks and the complex domain dominated by known unknowns and order.

Systems theory has three main branches: hard systems, soft systems, and dynamic systems (Yawson, 2013). Systems that rely on computer simulations and a restricted focus on the transformation of inputs into outputs in pursuit of predetermined goals and objectives are called "hard systems". The hard systems are characterised by their focus on objective, quantifiable problems that can be addressed using models and optimization techniques, generally rooted in the belief that systems can be understood and controlled through deterministic rules and structured methodologies (Powell, 2018). Systems that are difficult to quantify are called "soft systems" (Powell, 2018). Cases involving parties with contrasting worldviews have benefited greatly from its utilisation. It takes into account the qualitative and quantitative aspects of a problem situation and is used to gain insight into people's intentions, perspectives, and interactions. Systems thinking is a way of looking at the structure of dynamically complicated social systems (Cechvala, 2024). Critical systems inquiry is used with soft system approaches to form dynamic systems. Open and complex, dynamic systems have an innate tendency to change or evolve through time; this is one of their defining characteristics as evolutionary systems (Bánáthy, 2000).

2.3.3 Overview of complexity theory

The complexity theory facilitates comprehension of manufacturing firms that are complex adaptive systems, particularly during turbulence. It assumes that instability and unpredictability are the norm; therefore, successful endeavours in difficult times must accept change and use it to their advantage. Roughly 30 years ago Johnson and Burton, (1994), argued on chaos theory and its near relative complexity theory after seeing increased trends in their features in the social scientific literature, including studies of organisations. Smith (2003) posited that conceptual seminal work for complexity theory was laid down by researchers in biology and physical systems science and later by researchers in organisational science, and it is widely assumed that its rising popularity among managers is the result of changing environmental factors. Zeynab and Mehrzad (2017) advanced that complexity theory is a theoretical foundation for the ecosystem of a manufacturing firm's operations. Turner and Baker (2019) argued that complexity theory is developed further and recognised as offering a fresh outlook and a novel approach to theorising. These enhancements may allow researchers to better address the complexities of future technological innovation, globalisation, complicated market dynamics, cultural shifts, and other possibilities and problems.

Complexity theory facilitates comprehension of manufacturing firms that are complex adaptive systems, particularly during turbulence. Namaki (2018) argued that complexity theory conveys to a firm's management that the era of hierarchical (predefined) objectives, predetermined logic, and precise control is over. Complexity theory assumes that instability and unpredictability are the norm, and so successful endeavours during difficult times must accept and use change to their advantage (Byrne & Callaghan, 2022). However, in reality, complexity theory is anything but straightforward because there is no single unifying theory. Instead, many different hypotheses on complex systems come together under the umbrella of complexity studies. It in particular, remains underexplored in manufacturing despite the growing interest (Vidal & Hernández, 2021).

Due to the extensive cross-fertilisation of complexity theories, its true character remains elusive to scholars (Manson, 2001). Some of the complexity theories include deterministic complexity, algorithmic complexity theory, and aggregate complexity theory. A firm transitions from a complicated style of resolving day-to-day issues to a more complex mode of operation that changes and adapts to its internal and external environment. The

notion of complexity acknowledges that economic and organisational phenomena resemble those found in science and nature. The most effective way to comprehend the resemblance is to examine the fundamental characteristics of complex systems: growing returns, self-organising processes, continual adaptation, sensitivity to initial conditions, and nonlinearity (Sammut-Bonnici, 2014). An essential objective of assessments of complex systems is to acquire an understanding of the various interactions that operate inside a system to achieve particular dependent outcomes. Nevertheless, the very nature of complex systems dictates that the more complex the system, the more difficult it is to find the significant interactions or pivot points (Messina et al., 2008). This underscores the importance of understanding and managing uncertainty within firms, as uncertainty is an increasingly important concept requiring a thorough evaluation. This is not a surprise, as manufacturing complexity may rise in today's globalised and interconnected market due to the ebb and flow of demand and the accompanying demands for high product quality, low cost, short lead time, and high customisation (Efthymiou et al., 2016). According to the context, complexity can be classified as either physical or functional. What is meant by "complexity" in the functional domain is the degree to which it is not known whether the needs will be met or not.

Similar to the design of manufacturing systems, this level of complexity can be further broken down into time-independent and time-dependent subsets. Uncertainty resulting from the designer's lack of information or understanding of the system and its components is one source of time-independent complexity, along with failure to fully always satisfy the functional needs of the system. On the other hand, the complexity that depends on the passage of time can be either combinatorial—increasing as a function of time because the number of possible combinations of states grows exponentially with time—or periodic—existing in a finite time period with a finite number of possible combinations of states.

Static and dynamic manufacturing complexity are two more categories that can be broken down in the physical domain. Static complexity, also known as structural complexity, is concerned with the structure and configuration of the system, the number and variety of products, and the number and variety of components within the system, including humans, machines, buffers, and transportation systems. The chance that a system is in control during a given time period (referred to as dynamic or operational complexity) is related to the uncertainty of the system's behaviour throughout that time period

(Papakostas et al., 2009). The complexity theory facilitates comprehension of firms that are complex adaptive systems, particularly during turbulence. It assumes that instability and unpredictability are the norm; therefore, successful endeavours in difficult times must accept change and use it to their advantage (Burns, 2015).

Smith and Humphries, (2004) also highlighted the complex theory as a management tool. The complexity theory is immersed in manufacturing systems (Vidal et al., 2023). Due to its versatility and relevance today, complexity theory can be applied in different research fields. Woodside (2014,p.2496) notes, "The literature on complexity theory is expansive and heads in several discernable directions." The complexity theory has been applied in organisational science studies (Anderson, 1999; Woodside, 2014). Turner and Baker (2019) argued for the usefulness and application of complexity theory in social sciences. These authors explain that complexity theory can provide a new perspective and method for social science disciplines. This can enhance the social sciences' ability to address the complexity that arises from technological advancement and globalisation and their challenges and opportunities.

Turner and Baker (2019) reviewed more than 30 references to cite the application of complexity theory in 20 contexts within social science disciplines.² Pavlov and Micheli (2023) also highlighted the application of complexity theory when addressing contemporary issues within the organisational performance management field and its usefulness in mapping forward its future development. Likewise, Woodside et al., (2018) also provided a perspective on the application of complexity theory for identifying and modelling anomalies in a firm. These authors advanced the use of complexity theory for modelling outcomes rather than directionality, and modelling complex rather than simple outcomes. It is clear that system complexity and uncertainty are linked, and competent system analysis is needed to build foundations and manage operational uncertainty. According to Sammut-Bonnici (2014), similarities are best understood by examining complex systems' rising returns, self-organising processes, continuous adaptation, sensitivity to initial conditions, and nonlinearity. In the functional domain, "complexity" means the degree to which needs may not be supplied. This level of complexity can be

² Turner, J. R., & Baker, R. M. (2019). Complexity Theory: An Overview with Potential Applications for the Social Sciences. *Systems*, 7(1), 4. <https://doi.org/10.3390/systems7010004>. Table 3 Complexity theory application

divided into time-independent and time-dependent subsets, like manufacturing system design.

Complexity theory highlights the unpredictable nature of complex systems due to their nonlinear dynamics, feedback loops, and sensitivity to initial conditions (Kemp, 2009). Although it emphasises the importance of adaptation, it offers limited predictive power, making it difficult for practitioners to foresee specific outcomes (Cilliers, 2000). This author argued that complex systems are inherently unpredictable because of their interconnections and feedback loops. Complexity theory emphasises emergent properties that arise from interactions between system components. However, this can sometimes obscure the role of intentional, top-down interventions or control mechanisms, which are still critical in many real-world scenarios (Stacey, 2015). Although complexity theory focuses on understanding intricate interactions within systems, this can sometimes lead to overcomplicating problems that could be solved using simpler and more direct approaches (Snowden, 2005). This author suggests that not all problems require complex approaches and that simpler frameworks may sometimes suffice. Complexity theory has been applied to management (Massa et al., 2018; Snihur & Tarzijan, 2018; Vatankhah et al., 2023) including operations management (Maylor & Turner, 2017; Okwir et al., 2018; Reyes, 2013; and operations research (Kruger et al., 2019;; Petropoulos et al., 2024; Schirmer, 1995) showing its applicability to this study.

2.3.4 Selection of relevant grounding theory

Grounding principles and underlying assumptions are used to compare the selected theory/theories appropriate to this study (Table 2.1). For the contextualising theory, the selection criteria employed were the dominant mode of inquiry, attributes relationship, and primary mode of change (Meyer et al., 1993a; Meyer, Tsui, et al., 1993b).

Table 2.1: Grounding principles and underlying assumptions of the grounding theories

Grounding principles and underlying assumptions	Description	Chaos theory	Systems theory	Complexity theory
The dominant mode of inquiry	Approach to develop, test and refine theory	Deterministic to non-deterministic (Biswas et al., 2018; Goulielmos, 2019; Lartey, 2020)	Reductionist to non-deterministic (Turner & Baker, 2019)	Non-deterministic (Grobman, 2005)
Attributes relationship	Connection and linkage of attribute relationships	Nonlinear (Biswas et al., 2018; Lartey, 2020; Levy, 2007)	Linear (Turner & Baker, 2019)	Nonlinear (Gear et al., 2018)
The primary mode of change	Modification and evolution of theory over time in response to development and emerging insights	Frame-breaking change (Biswas et al., 2018; Lartey, 2020)	Emergent and adaptive	Emergent (Gear et al., 2018)

Source: Author

2.3.4.1 The dominant mode of inquiry

The dominant mode of inquiry is regarded as the approach to develop, test, and refine theory. For these analysed theories, the dominant modes of inquiry are deterministic to non-deterministic for chaos theory (Biswas et al., 2018; Goulielmos, 2019; Lartey, 2020), reductionist to deterministic for system theory (Turner & Baker, 2019), and non-deterministic for complexity theory (Grobman, 2005). The inquiry into determinism pertains to scientific theories and serves as a significant tool for evaluating theories across multiple dimensions (Müller & Placek, 2018). The fundamental concept underlying the philosophical (metaphysical) concept of determinism posits that, based on the current state of affairs, a singular, inevitable outcome exists for the future (Müller & Placek, 2018). Inquiring about determinism is frequently a productive approach to enhancing one's comprehension of the theory, as numerous intricate technical matters must be tackled to render a judgment on the theory's deterministic nature. Chaos theory is mathematically meaningful, deterministic, linear, and sensitive to its original circumstances (Prigogine & Holte, 1993). The modern view holds that chaos contains structure, is highly complex, and has numerous patterns, similar to the weather and waterfalls. It looks to be random, but it is governed by deterministic principles (Goulielmos, 2019). Systems theory is always advancing to enhance comprehension and tackle the intricacies of the real world, particularly with global concerns and technological progress. The paradigm of systematic

thinking in non-determinism is a theoretical framework emphasising the importance of considering multiple possible outcomes and uncertainties when analysing complex systems (Turner & Baker, 2019). The modification and evolution of systems theory has increasingly focused on complexity, adaptability, and multidisciplinary applications. It has transitioned from deterministic, mechanistic models to acknowledge uncertainty, nonlinearity, and the adaptive capabilities of complex systems. Unlike the determinist method of inquiry, a non-determinist method of inquiry challenges the idea that phenomena are solely caused by causal links (Grobman, 2005). It welcomes complexity, uncertainty, and the potential for numerous consequences arising from the interaction of different elements. This mode of inquiry is particularly pertinent in disciplines that include complex systems. In complex settings, straightforward, linear epistemology is inadequate for addressing the challenges of this complexity (Turner & Baker, 2019). Dynamic theories such as complexity theory have a non-deterministic mode of inquiry. The subsequent resolution of systems theory is achieved through a systematic solution, namely the systems analysis theory.

2.3.4.2 Attributes relationship

The attributes relationship focuses on the connections and linkages the theory employs in research. These can be nonlinear, linear, unidirectional, linear, or reciprocal and nonlinear. Chaos and complexity theory subscribe to a nonlinear attribute relationship. The concept of chaos does not connote disorder but rather signifies the presence of unpredictability within a system that is characterised by evolutionary order (Smith, 2003; Lartey, 2020). Chaos theory investigates dynamic systems that exhibit nonlinear behaviour, intricate interconnections, and dynamic evolution over time. The implication is that a minor alteration in the starting state of a nonlinear dynamic system can yield a significant outcome. The presence of unexpected outcomes poses a challenge in predicting dynamic systems.

Chaos theory is a promising framework that accounts for the dynamic evolution of industries and the intricate interactions among industry participants (Levy, 2007). Firms are shown as nonlinear, dynamic systems that are vulnerable to forces of stability and forces of instability that drive them toward chaos (Biswas et al., 2018; Levy, 2007). In recent years, systems theory has been criticised for not being able to deal with complexity and nonlinear systems and for being too mechanical (Yorks & Nicolaides, 2012). The

major uncertainty principal concern is that by the time a dynamic problem is detected and analysed, the environment has changed, making the results irrelevant. System assessments aim to understand how system interactions affect dependent outcomes. However, systems that are complex make it harder to detect key interactions or pivot points (Messina et al., 2008). Traditional change management strategies no longer work in complex and chaotic systems. Thus, business managers must constantly monitor their evolution. The firm moves from a convoluted approach to daily problems to a more complex one that adjusts to its internal and external surroundings.

2.3.4.3 The primary mode of change

A theory's primary mode of change is about the modification and evolution of theory over time in response to development and emerging insights into aspects of the system under study. The mode of change for chaos theory is frame-breaking change (Biswas et al., 2018; Lartey, 2020). Frame-breaking change denotes a form of organisational transformation that fundamentally modifies the prevailing structure, strategy, processes, or culture of an organisation. It undermines the foundational ideas and operations that delineate the organisation's functioning. This type of change frequently necessitates a comprehensive re-evaluation of organisational operations, demanding transformational transformations instead of incremental modifications. Frame-breaking change exhibits features of discontinuous change, in contrast to progressive or incremental change, as it is both abrupt and profound. This is a comprehensive alteration that impacts various aspects of the organisation. It is frequently instigated by crises so that transformative change may be propelled by external factors such as market disruption, technical advancement, or economic turmoil that compel the organisation to reevaluate its core strategy.

The primary mode of change in complexity theory is emergent change (Gear et al., 2018). Emergent change refers to a form of organisational transformation that is neither premeditated nor imposed by higher management but instead develops naturally and incrementally within an organisation, frequently as a reaction to a volatile and unpredictable environment. In contrast to planned or deliberate change, which is propelled by strategic decisions, emergent change is characterised by spontaneity and adaptability and is influenced by individuals within the organisation as they react to challenges, opportunities, or environmental shifts resulting from dynamic changes within

their operational environment. Emergent change generally arises in reaction to alterations in the external environment, such as fluctuations in market needs, technical innovations, regulatory modifications, or competitive pressures. It enables organisations to maintain adaptability and responsiveness to unplanned or unforeseen changes. Emergent change can be both gradual (little, continual modifications) and, over time, transformative. Similar to complexity theory, the primary mode of change in system theory is emergent and adaptive. However, it may differ based on the system type and context. Systems theory focuses on comprehending the relationships and interactions among components within a system and how these interactions facilitate change throughout time. Changes in systems theory frequently result from the system's internal dynamics and external pressures, emphasising the system's adaptation, evolution, and occasional transformation in response to these influences.

Based on these grounding principles and underlying assumptions, complexity theory was selected as the grounding/contextualising theory, as it is a non-deterministic, nonlinear, and emergent mode of change.

2.4 Operationalising theory

Two theories were evaluated to select the operating theory of the study. These were the contingency theory (Donaldson, 2001; Lee et al., 2022; Sambamurthy & Zmud, 1999) and the configurational theory (Fiss et al., 2013; Pla-Barber et al., 2020).

2.4.1 Contingency theory

Fiedler (1964) posited that the origins of the contingency theory lie in the discipline of organisation theory. Behavioural research acknowledges that an organisation must be compatible with its environment and context. Therefore, various optimal decisions exist depending on the dominant forces in each of these circumstances. Galbraith (1973) synthesised the early research on contingency theory and asserted that the fundamental assumptions of contingency theory are that there is no single best way to organise and that not all methods of organising are equally successful. This is more important within an operating environment influenced by multiple factors.

Sambamurthy and Zmud, (1999) differentiated three categories of contingencies based on the impact of the contingency factors on the outcome. In the case of reinforcing contingencies, all contingency elements result in the same outcome. Similarly, dominant

contingencies produce a single outcome, but the outcome is contingent on a single fundamental contingency element. In contrast, conflicting contingencies do not permit a predominating outcome, as the many contingency elements necessitate divergent management decisions. Lumpkin and Dess (1996) argued that the fundamental tenet of contingency theory suggested that a 'fit' between variables is crucial for achieving good performance. Lee et al., (2022) argued that contingency theory initially focuses on elucidating the concept and operationalising contingency variables concerning stance movement. The focus then shifts to examining the relationship between contingency variables and stance. The contingency theory proposes that some managerial practices are better suited to particular contexts, given that managing procedures are not always appropriate in all scenarios. Contingency theory suggests that routines help to improve performance based on the characteristics of the environment.

A good match, when selected, produces the desired results (Donaldson, 2001; Romero-Silva et al., 2024). The contingency is applicable in operations management (Donaldson, 2001; Gamede & Mtotywa, 2022) including quality management and supply network management and supply chain efficiency (Raita, 2021). It applies to corporate and entrepreneurial firms (Linton, 2014) and to the present research, which focuses on the influences of operations management on product and service firms. To do this, firms must first identify the most important aspects of contingencies influencing the scenario and then adjust their theories and practices accordingly. A firm's success depends on several variables, such as the laws and customs of the country in which it works, the nature of the industry in which it operates, and the nature of its employees - incentive structures that motivate manual labourers may not motivate knowledge workers. Managers who excel in their jobs are adept at reading the nuances of every given circumstance to ascertain the best course of action. This highlights that contingency factors can be internal or external to the firm, situational or contextual factors (Matyusz, 2014). As Alves et al. (2017) pointed out, contingency theory, climate-change contingencies at the supply-chain level, firm structure for low-carbon management, as well as the practices and advantages of low-carbon operations management are all complicated to integrate but a necessity within the firm.

The early criticism of contingency theory was that its concept was not clear, and the relationships between the concepts were not stated adequately (Miller, 1981; Schoonhoven, 1981). Without properly defined ideas (i.e., those that have attained a level

of consensus definition), empirical research cannot identify the correlations between variables. Three crucial dimensions require refinement: (a) effectiveness, (b) environment, and (c) consistency. According to this theory, organisations should transform into structures that are suitable for the experiential contingencies they face. These contingencies may vary on dimensions such as the operating environment, which may include complexity and dynamism, the task at hand, and the technological landscape. A critique of the so-called universal method, which had previously predominated in the field of management science, gave rise to the contingency theory. That is to say, a number of academics questioned the concept of there being "one optimal way." The central notion of fit in contingency theory postulates that the performance of an organisation will be improved if the various components that make up the organisation, both internal and external, are aligned.

The contingency theory also posits that certain work structures clearly outperform available substitutes for specific kinds of tasks, environmental conditions, or combinations of the two and that shifts that occur within these structures over time represent organisational adaptation. Moreover, the contingency theory proposes that this organisational adaptation can occur in various contexts (Westwood & Clegg, 2003). Therefore, the emergence of work structures within organisational teams that place emphasis on peer-to-peer relationships can be modelled within a contingent-theoretical framework consisting of structure, contingency such as task complexity, knowledge sharing, task routineness, and performance effectiveness of output in relation to the goal. In brief, according to contingency theories, different situations will call for different types of management (Moniz, 2010).

2.4.2 Configurational theory

The configurational theory has a long history in the fields of strategy and organisational studies (Meyer et al., 1993b). Literature has delineated the value of employing configurations (sometimes referred to as gestalts, archetypes, or generic types) to cultivate an area of empirical interest (Miller, 1986). Configurations serve to evaluate multiple factors while preserving a significant and coherent aspect of organisational reality and providing a complete framework for a subject (Ambrosini et al., 2009).

Misangyi et al., (2017) posited that the origin of configurational research involves organisational studies which were inspired by systems thinking. Note that, at the time,

scholars did not name it "configuration"; nevertheless, they conceptualised organisations as complex systems (Boulding, 1956). Dess et al. (1997) argued that configuration is a set of interrelated elements or objects that spans more than one domain. Compared to the contingency approach, which is limited to analysing the interaction between two domains, the configuration approach is able to draw from more detailed models due to its ability to analyse more than two domains simultaneously, such as structures, strategy, and environment, crucial in the analysis of complex environments (Matyusz, 2014). This is because the relationships between variables exhibit inherent complexity, occasional nonlinearity, and abrupt shifts that can lead to diverse consequences and outcomes (Woodside, 2017). Dess et al. (1997) argued that configuration is a set of interrelated elements or objects that span more than one domain.

Configurational theorising is centred around three fundamental principles: (1) conjunctural causation - other factors influence the impact of one factor; (2) equifinality - different combinations of factors might result in the same outcome; and (3) causal asymmetry - causes that result in the presence of a particular outcome may differ significantly from the causes that result in the lack of that outcome (Iannacci & Kraus, 2022; Pattyn et al., 2022). The configurational theory presents several concerns that researchers must consider (Park & Mithas, 2020). These concerns include the identification of causal processes, the robustness of findings under varying assumptions, the capacity to facilitate theoretical exploration and testing of causal relationships, and the capability to manage large samples and coarse-grained data. Configuration theorising is structured to be responsive to variations in consistency, frequency, and calibration thresholds (Rutten, 2020). These scholars have recommended either revisiting the cases for small sample sizes or re-examining the data for large sample sizes to assess the robustness of the original findings. An associated concern is the matter of endogeneity (Meuer & Fiss, 2020)

2.4.3 Selection of operationalising theory

Grounding principles and underlying assumptions shape the framework within which theories are developed and applied, influencing their relevance and effectiveness in real-world scenarios. These principles and assumptions were used for the selection, including the dominant mode of inquiry, attributes relationship, the primary mode of change, mechanism of the operation, equilibrium assumptions, and effectiveness assumptions

(Meyer et al., 1993a; Meyer et al., 1993b). Aspects of these theories are presented in Table 2.2. These foundations determine how knowledge claims are validated—whether empirically, rationally, or critically—affecting the theory's adaptability to diverse contexts (Pérez-Hämmerle et al., 2024). Nkwake (2013) stressed the importance of assumptions, arguing that if they are ambiguous, they may lead to misinterpretations or ineffective applications, as the strength of a theory's application is contingent upon the robustness of its foundational assumptions.

Table 2.2: Grounding principles and underlying assumptions of operationalising theories

Grounding principles and underlying assumptions	Description	Contingency theory	Configurational theory
The dominant mode of inquiry	Approach to develop, test and refine theory	Reductionists (Meyer et al., 1993b) Situational and context-dependent (Reinking, 2012)	Holistic Meyer et al. (1993b); Fiss (2011; Iannacci & Kraus, 2022)
Attributes relationship	Connection and linkage of attribute relationships	Unidirectional and linear (Nassou & Bennani, 2024) (Van De Ven et al., 2013)	Reciprocal and nonlinear (Meyer et al., 1993a; (Fiss, 2011)
The primary mode of change	Modification and evolution of theory over time in response to development and emerging insights	Incremental change (Alsamhi et al., 2022; Mark & Erude, 2023; Mendy, 2020; Nassou & Bennani, 2024)	Frame-breaking change Meyer et al. (1993b)
Operational mechanisms	Mechanism (methods and procedures) for evaluation, testing and validation of theory	Mainly symmetrical	Mainly asymmetrical
Equilibrium assumptions (Response)	Premise towards stability or balance in certain conditions.	Quasi-stationary equilibrium	Punctuated equilibrium
Effectiveness assumption	The premise is to accurately describe, predict, or explain phenomena within the applicability domain - value and usefulness.	Situational and context-dependent (Reinking, 2012)	Equifinality (Fiss et al., 2013; Misangyi et al., 2017)

Source: Author

2.4.3.1 The dominant mode of inquiry

Meyer et al. (1993b, p. 1177) had earlier argued that the contingency theory's dominant mode of inquiry is reductionist: "Contingency research invokes reductionism as its

dominant mode of inquiry." This dominant reductionistic mode of inquiry pertains to a philosophical and scientific approach that emphasises the reduction of complex systems or issues into their fundamental components or elements. The reduction is utilised as a scientific approach to investigating complex systems (Dafermos, 2015; Jones, 2000). Floridi (2008) posited that the reductionist approach extracts what is essential to understanding the system and its dynamics from the wide variety of proposed theories and explanations. More recently, there has been more emphasis on the contingency being situational and context-dependent (Reinking, 2012). The transitions are not surprising, as Nassou and Bennani (2024) explained that contingency theory has undergone dynamic evolution, marked by different conceptual phases.

On the other hand, configurational theory's dominant mode of inquiry is holistic and explores the whole system. (Meyer et al., 1993b) highlighted that the configurational theory has the advantage of being able to analyse complicated problems because of its multidimensional and holistic nature as it (1) concentrates on the ways in which environment, structure, and strategy actions can be matched to obtain superior performance, and (2) accounts for the intricate interconnectedness of multiple elements, nonlinearities and discontinuities. This implies that there could be a complementary relationship between these features in configurations, where each trait either strengthens the impact of the other or makes up for the shortcomings of the other.

Therefore, it is not necessary for all attributes to be present in every configuration. This concept is called equifinality, which means that multiple combinations might be equally successful in producing the same outcome (Fiss et al., 2013; Misangyi et al., 2017). Flynn et al. (2010) demonstrated the complementarity of the contingency and configurational theories in the analysis of supplier integration. Franco et al., (2023) also argued that contingency theory could explain the connections between supply relationships; however, research recommended configurational theory for configurations of practices to develop an approach to responding to contingency factors.

Within the context of the present research, the complexity theory was used as a grounding or contextualising theory, while configurational theory was used as the operationalising theory.

2.4.3.2 Attributes relationship

The connection and linkage of attribute relationships in contingency theory is unidirectional and linear (Meyer et al., 1993b; Schoonhoven, 1981), while that of configurational theory is reciprocal and nonlinear (Meyer et al., 1993a). In contingency theory, the linearity assumption has been a cornerstone, but as firms face increasingly complex environments, the need for more nuanced models has become apparent. Several authors have argued that the linearity assumption of contingency theory can be adjusted to more accurately represent complex organisational dynamics (Nassou & Bennani, 2024; Van De Ven et al., 2013). Nassou and Bennani (2024) posited that this could be done using the configurations approach as it underscores a holistic perspective of organisations, acknowledging many structural archetypes and the complex interactions of multiple contingency elements. This facilitates an improved comprehension of the interplay between the attributes (constructs), indicating that a nonlinear approach may more effectively capture inherent complexities. There was always clarity and agreement on the nonlinearity of the configurational theory (Fiss, 2011)

2.4.3.3 The primary mode of change and operational mechanism

The primary mode of change, which entails modifying and evolving theory over time in response to development and emerging insights, is incremental for the contingency theory, while it is a frame-breaking change for configurational theory. Thus, contingency theory offers a framework for understanding how various factors influence organisational structure and control mechanisms, making it applicable to predicting outcomes of incremental change initiatives (Mendy, 2020; Nassou & Bennani, 2024). Amhalhal et al. (2022) supported by Mark and Erude (2023), argued that applying contingency theory can help predict outcomes of incremental changes by considering specific organisational contingencies, thereby enhancing the likelihood of successful implementation and performance improvement in diverse settings. This is different from configurations which use frame-breaking.

Frame breaking as a mode of change in manufacturing significantly influences the development of the configurational theory by challenging existing paradigms and necessitating new frameworks to accommodate dynamic and flexible manufacturing systems. This approach involves rethinking traditional manufacturing processes to adapt to rapid changes in market demands and technological advancements. The integration of

frame breaking into the configurational theory allows for a more comprehensive understanding of how manufacturing systems can be reconfigured to achieve optimal performance and sustainability (Miller, 1986).

Operational mechanisms highlight the mechanisms (methods and procedures) for evaluating, testing, and validating theory (Meyer et al., 1993a). The contingency theory mainly applies a symmetrical mechanism, while the configurational theory mainly applies an asymmetrical mechanism.

2.4.3.4 Equilibrium and effectiveness assumptions

Equilibrium assumptions are a response and provide a premise for stability or balance under certain conditions, while effectiveness assumptions discuss the premise of accurately describing, predicting, or explaining phenomena within the applicability domain - value and usefulness (Meyer et al., 1993a). Contingency theory is situational and context-dependent (Reinking, 2012), while configurational theory is based on equifinality. Equifinality highlights that more than one combination might be as successful in generating the same result (Fiss et al., 2013; Misangyi et al., 2017). Based on the dominant mode of inquiry, attributes relationship, the primary mode of change, mechanism of the operation, equilibrium assumptions, and effectiveness assumptions, the configurational theory was selected and used as the operationalising theory of this research.

2.4.4 Configurational theory in manufacturing

The configurational theory has been used within manufacturing studies in different focus areas (Table 2.3). These include strategic alignment for high performance (McCarthy & Tsinopoulos, 2003; Pla-Barber et al., 2020). The theory supports the development of agile manufacturing strategies, allowing firms to adapt to changes and maintain competitive advantage.

Table 2.3: Configurational theory used in manufacturing

Focus area or themes in manufacturing	References
Strategic alignment for high-performance	Damke et al. (2018); McCarthy and Tsinopoulos (2003); Pla-Barber et al. (2020)
System configuration for flexibility and adaptation	Chang and Park (2018); Zheng et al. (2019)
Product configuration and Customisation	Qiao et al. (2019); Kristjansdottir et al. (2017)

Source: Author

Pla-Barber et al. (2020) studied achieving high performance by aligning their strategies with environmental conditions. Research has been published on system configuration for flexibility and adaptation (Chang & Park, 2018; Zheng et al., 2019). The configurational theory is applied in the design of systems for manufacturing, reducing the complexity of selecting suitable configurations from numerous alternatives (Zheng et al., 2019), and in reconfigurable manufacturing systems where the configurational methods clarify the logical relations and hierarchical design processes, improving response capability and design efficiency. Chang and Park (2018) advanced the use of configuration, space-based, discrete event system specification in smart factories, which allows for real-time flexibility and the handling of production turbulences to better describe and manage complex manufacturing systems. The configurational theory in manufacturing emphasises the adaptability and dynamic reconfiguration of production systems to meet varying product requirements, thus supporting self-configuration.

Studies are also advanced in product configuration and customisation. Kristjansdottir et al. (2017) studied how configurational theory aids in using configurators to automate product specification and sales processes while manufacturers meet customer demand, ensuring increased efficiency and customer satisfaction. Qiao et al. (2019) also conducted studies on manufacturing configurational theory, explaining how improved design can assist with manufacturing efficiency. These studies underpin the use of the configurational theory in manufacturing and further strengthen the relevance of this operationalising theory in this research.

2.5 The linkage between complexity and configurational theories

Complexity theory and configurational theory are two distinct approaches to understanding complex systems, each with its own focus and methodology (Misangyi et al., 2017). Complexity theory generally emphasises dynamic interactions within systems and emergent properties (Byrne, 2005; Leydesdorff, 2008) while the configurational theory focuses on the specific arrangements or configurations of elements within a system that lead to particular outcomes (Iannacci & Kraus, 2022). Thus, complexity theory often emphasises intricate interdependencies and dynamic interactions within systems, focusing on how these elements contribute to emergent behaviours. In contrast, configurational theory specifically addresses causal complexity by identifying and analysing distinct configurations of explanatory factors that lead to particular outcomes. While complexity theory may explore a broader range of interactions, configurational theory seeks to simplify and categorise these interactions into coherent configurations, facilitating a clearer understanding of how specific combinations of factors produce specific results (Furnari et al., 2021)

Both theories offer valuable insights into the study of complex phenomena, but they differ in their conceptual frameworks and analytical techniques. Complexity theory often employs simulation models and dynamic systems analysis to study emergent behaviours, while configurational theory uses set-theoretic methods such as QCA to identify and analyse configurations (Byrne, 2005; Park & Mithas, 2020). In configurational theory, the reduction of uncertainty is a key aspect, as configurations are seen as a way to stabilise and globalise system interactions, providing a measure of synergy within complex systems (Leydesdorff, 2008). Based on this analysis, the present study is grounded on the theories of complexity (Sammut-Bonnici, 2014; Zeynab & Mehrzad, 2017) and configurations (Fiss et al., 2013; Pla-Barber et al., 2020). Complexity provides an overarching high-level view, which can then be detailed using configurational theory.

Complexity theory presents multiple notions that can be used in conjunction with various existing theoretical frameworks to view complex phenomena in various ways (Eppel, 2017). This enables a transdisciplinary approach to a study, combining multiple bodies of knowledge to create a more comprehensive understanding of complicated situations (Gear et al., 2018). Current and future research might benefit from understanding complexity in order to make sense of such phenomena as cutting-edge

technology, internationalisation, complex markets, and cultural shifts. In a nutshell, the study of complexity can assist in meeting the problems and seizing the opportunities of a new era (Snowden & Boone, 2007). The most effective way to comprehend the resemblance is to examine the fundamental characteristics of complex systems: growing returns, self-organising processes, continual adaptation, sensitivity to initial conditions, and nonlinearity (Sammut-Bonnici, 2014).

Table 2.4 presents the core tenets of complexity and configurational theories, with the main ones being emergence, casual asymmetry, and a growing view on equifinality in complexity theory. (Turner & Baker, 2019) also included irreducible, self-organising and adaptive. For the configurational theory, it is mainly causal asymmetry, conjunctural causation, and equifinality with the emergence of a contrary view.

Table 2.4: Core tenets of the complexity and configurational theories

Core tenet	Complexity theory	Configurational theory
Emergence	Byrne (2005); Leydesdorff (2008); Turner & Baker (2019)	
Causal asymmetry	Fiss (2013); Prentice (2020)	Iannacci and Kraus, (2022)
Conjunctural causation		Huang et al. (2024); Iannacci and Kraus (2022); Van Nguyen et al. (2024)
Equifinality	Mele et al. (2010) Woodside (2014); Zhang (2010)	Furnari et al. (2021); Pla-Barber et al. (2020); Woodside (2014)

Source: Author

2.5.1 Emergence

The emergence core tenets is mainly associated with the complexity theory (Byrne, 2005; Leydesdorff, 2008; Turner & Baker, 2019). Gear et al. (2018) explain that the emergence occurs when systems properties or levels of complex organization generated by agent self-organisation. Zheng (2021) highlighted the emergence in complex systems, which is characterised by new collective behaviours that arise from interactions among system elements and cannot be produced by a single unit. Yuan et al., (2023) argue that emergence and causality are interconnected, with new causality arising at higher levels of abstraction that cannot be attributed to individual properties alone. Emergence occurs

in firm transformation which is mainly not premeditated nor imposed by firm management. The emergent change generally arises in reaction to external environment alterations which can range from market needs fluctuations, regulatory modifications, or competitive pressures (Gear et al., 2018). Emergent change enables firms to maintain adaptability and responsiveness to unplanned or unforeseen changes. Emergent change can be both gradual with continual modifications and/ or transformative over time.

2.5.2 Causal asymmetry

Fiss (2011), later supported by Prentice (2020), posited that relationships between constructs can be nonlinear, allowing for causal asymmetry where the same antecedent can lead to different outcomes depending on the context. Simply put, the causal asymmetry is assumed when the presence and absence of the outcome require different explanations (Glaesser, 2024). Causal asymmetry is a core tenet of both complexity (Prentice, 2020) and configurational theories (Iannacci & Kraus, 2022). Miller (1986) argued that understanding the complexity of organisations requires arrangements comprising numerous aspects. They facilitate the comprehension of extensive, intricate, and substantial data. As such, utilizing complexity and a configurational theory approach presents an opportunity to comprehend in detail the patterns generated by these conditions (El Sawy et al., 2010; Zeynab & Mehrzad, 2017).

These theories are characterised by multiple principles or core tenets of equifinality (Woodside, 2014). Equifinality highlights that more than one combination might be as successful in generating the same result (Fiss et al., 2013; Misangyi et al., 2017). Configurations possess predictive capabilities, enabling an organisation to utilise varying perspectives on knowledge as a tool to assess its current standing and to identify potential future positioning. A firm's existing knowledge configuration may impede its ability to realise future strategies; for instance, a small, family-owned business possesses distinct knowledge capabilities. Miller (1996, p510) posited that a configuration can serve as a "greater source of competitive advantage than any single aspect of strategy."

2.5.3 Conjunctural causation

The conjunctural causation is a core tenet of configurational theory (Misangyi et al., 2017). Configuration approaches posit conjunctural causation so that each condition typically lacks a distinct effect on the outcome; rather, its influence may

manifest only in conjunction with other conditions. This contrasts with theoretical variance models, which believe that each variable exerts a distinct influence on the outcome (Huang et al., 2024). As such, configurational theory shifts focus from correlational to configurational approaches, embracing equifinality and conjunctural causation where different combinations of conditions can lead to the same outcome.

2.5.4 Equifinality

Complexity theory is characterised by the principle of equifinality (Woodside, 2014; Zhang, 2010), as is configurational theory (Furnari et al., 2021; Pla-Barber et al., 2020; Woodside, 2014). The utilisation of complexity and configurational theory approach presents an opportunity to comprehend in detail the patterns generated by these conditions (El Sawy et al., 2010; Zeynab & Mehrzad, 2017). Within the context of the present study, multiple routes can be used to improve the firm's sustainable performance (Prentice, 2020). Gresov and Drazin (1997) suggested that equifinality refers to a state where a system can attain an identical end state through various pathways and distinct initial conditions. Simply put, not all attributes need to be present in each configuration; this concept is known as equifinality, and it refers to the idea that more than one combination might be as successful in generating the same result (El Sawy et al., 2010; Fiss, 2011). Because of this, they are ideally suited for theories that focus more on the middle ground and are attentive to their surroundings. Gresov and Drazin (1997) highlighted four types of equifinality based on the latitude of structural options and the degree of conflict in functional demand. These include ideal profiles, suboptimal equifinality, trade-off equifinality and configurational equifinality and are indicated in Figure 2.2. The present study subscribes to configurational equifinality. Configurational theory emphasises an archetypal or holistic pattern in which most of the necessary conditions for an event are interconnected rather than independent (Fiss, 2011). Thus, the concept of equifinality is a viable construct for exploring diverse causal trajectories that culminate in comparable outcomes, irrespective of the initial circumstances.

The development of an equifinality perspective was a significant contribution towards advancing the integration of systems theory and management. This perspective offered a solution to the challenges of achieving goals in complex systems, addressing both the "how" and "in what way" aspects of the problem (Kapsali (2013). Zhang (2010) posited that by recognising equifinality, manufacturers can explore different operational

approaches, thereby enhancing flexibility and resilience. This is supported by Prentice, (2020), who argued that in manufacturing, multiple pathways can lead to the same outcome, such as product quality or operational efficiency. Recognising equifinality allows manufacturers to explore diverse approaches to problem-solving and innovation, ultimately enhancing adaptability and resilience in dynamic market conditions.

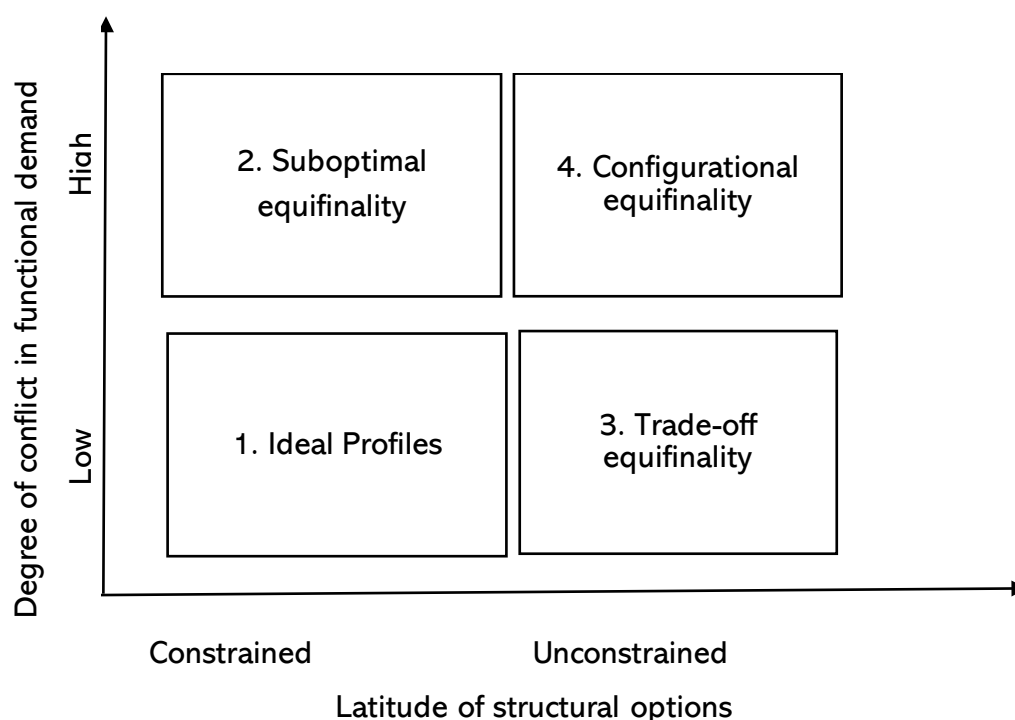


Figure 2.2: Types of equifinality

Source: Gresov and Drazin (1997).

2.6 Chapter conclusion

Grounding and operationalising theories are interrelated in a research process; grounding theory establishes the conceptual foundation, while operationalising theory facilitates the practical application of that theory in research. This chapter provided a systematic approach to selecting complexity theory as the grounding theory and configurational theory as the operationalising theory for the research. Their application and limitations are discussed in this chapter, and a detailed analysis of the use of configurational theory in manufacturing is also provided. These theories are linked; this was confirmed by their shared tenets, particularly causal asymmetry and equifinality. The configurational analysis and its linkage to QCA as a method are also explained in this chapter, with details of the

configuration. The causal conditions and outcomes of the study are discussed in Chapter 3, and the theory and methodological positioning and integration with QCA are discussed in Chapter 4.

Chapter 3

Literature Review of Configurations – Causal Conditions and Outcome

3.1 Introduction

Configurations are a specific set of causal variables (constructs) that are deemed to have a synergetic nature, and these serve as a screen to indicate an observed outcome or an outcome of interest in research (Pappas & Woodside, 2021; Ragin, 2008a). Configurations can emerge conceptually or empirically; both are designed to characterise "what" configurations exist in organisations (Duberley & Burns, 1993; Fiss, 2007; Woodside et al., 2018). The present study posits that operational uncertainty dimensions, Industry 4.0 and 5.0 technologies, and organisational learning are key causal variables that are critical for an outcome of interest, which is sustainable performance during times of operational uncertainty. As a result, a firm transition from a complicated style of resolving day-to-day issues to a more complex mode of operation that changes and adapts to its internal and external environment. The notion of complexity acknowledges that economic and organisational phenomena resemble those found in science and nature.

An essential objective of assessments of complex systems is to acquire an understanding of the various interactions that operate inside a system to achieve particular dependent outcomes. Nevertheless, the very nature of complex systems dictates that the more complex the system, the more difficult it is to find the significant interactions or pivot points (Messina et al., 2008). This chapter discusses causal conditions such as operational uncertainty, Industry 4.0 and 5.0 technologies, and organisational learning, and their analysis leads to outcomes such as sustained performance.

This literature review is crucial in academic research, as it collects existing knowledge and assesses the state of the field of study (Linnenluecke et al., 2020). The study has identified a multi-faceted gap that is empirical, theoretical, and methodological in nature. Improving this situation is difficult, especially regarding developing theories that increase understanding (Mollah, 2019; Shepherd & Suddaby, 2017) of the management of operational uncertainty, its mitigation, and its influence on a firm's performance. It is

critical to initially exhaustively examine numerous contributions from various interconnected disciplines to identify the gap(s) that need to be addressed in the research study (Robinson et al., 2011). These research gaps serve as a reference point for conducting research (Müller-Bloch & Kranz, 2015; Wagner et al., 2022) that allows the integration of such a research gap together with emergent core tenets and propositions that are critical to building coherent and structured research.

3.2 Operational uncertainty

Operational uncertainty drives unpredictability in the performance and outcomes of production processes due to variable factors such as changes in starting material properties, equipment conditions, and external influences (Vlasenkov et al., 2023).

3.2.1 Concept and sources of operational uncertainty

Operational uncertainties exist at different levels, including the external environment, industry, and firm levels. Wong et al. (2011) explained that external environmental factors are grounded in external causes in which the firm cannot directly intervene. The present study investigated the sources of operational uncertainty, and nine sources of operational uncertainty were identified in this study. These included external environmental dimensions - geopolitical tensions (GPT), policy and regulatory uncertainty (PRU), the cost of living-driven consumer behavioural change (CLC), pandemic turbulence (PDT), and energy stability and security (ESS). At the industry level, these sources of uncertainty include skills for future industrial work (SFW) and the entrenchment power of large firms (EPL), while at the firm level, sources of uncertainty involve generational work behaviour and ethics (GWB) and process capability and variations (PCV).

3.2.1.1 Geopolitical tensions

Global geopolitical conditions exhibit profound shifts (Pan, 2018), as indicated by the emergence of China as an economic powerhouse (Bellamy & Williams, 2011) and the strengthening of Russia's post-Soviet Union era - both of which altered global power structures. This shift in power was exacerbated by increased tension between Western Countries (such as the United States of America and countries in Europe) and Russia due to the war in Ukraine (Levy & Leaning, 2022; Prohorovs, 2022). Within a brief period, political discourse and decisive actions in Europe were influenced by the dichotomy between the West and the East: reports from the Ukrainian front; NATO's expansion to

Finland and Sweden; military defence and readiness; border controls, barriers, and the closure of borders against Russia and its ally Belarus, as well as protectionism and the endeavour to sever supply chains with unstable or adversarial nations from the perspective of the Western world. Geopolitics, in its traditional sense, has re-emerged as a central focus in Europe's political and economic landscape, influencing decision-making.

An ongoing US-China trade war is also creating challenges for trade stability (Moosa, 2020). An in-depth industrial analysis by Zeng et al. (2022) showed that bilateral tensions and the trade war have hit sectors hard, particularly those with well-established supply chain links to China. Geopolitical tension also resulted from China's perception that the Taiwan/US relationship (Caldara & Iacoviello, 2022) undermined the 'One China' principle (McKinney & Harris, 2021). There is also a weakening relationship between the US and Saudi Arabia (Hokayem, 2022; Batrawy, 2023), as well as wars and trade blockages in the Middle East. The war in the Middle East resulted, among other effects, in the blockade of commercial ships, increasing voyager times and transportation costs (Faucon et al., 2023). The IMF PortWatch (2024) data show a continuous decrease in trade through the Suez Canal and Panama Canal, declining by 50% and 32%, respectively. This has led to disruptions in supply chains and alterations in key macroeconomic indicators (Figure 3.1)

These geopolitical tensions have disrupted global supply chains (Ali et al., 2024; Bednarski et al., 2023) and practically every industry and firm has been impacted by supply bottlenecks, resulting in increased purchasing prices. Furthermore, European gas and oil disruptions and increased inflation rates exacerbated these changes. Thus, some of the impacts on trade between emerging economies such as South Africa and key trading partners such as Germany were an increase in supply lead time and purchase prices that affected the economies of both countries (KPMG, 2022).

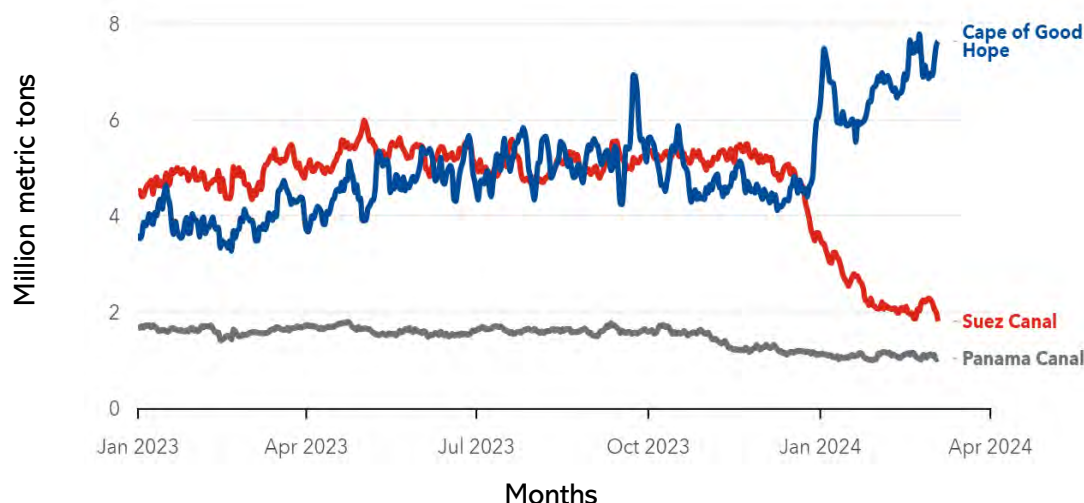


Figure 3.1: A 7day moving average of the daily transit trade volumes in metric tonnes

Source: IMF PortWatch (2024).

The South African manufacturing industry is highly influenced by geopolitical tensions at multiple levels. The imports have shown an upward trajectory, indicating increased imports to South Africa (Trading Economics, 2023). The increase in imports is expected to continue for the next few years. In December 2022, the main imports were machinery, which accounted for 21.3% of the total imports, mineral products at 16.9%, and chemicals at 12.6% (Trading Economics, 2023). All of these are part of the input-output of production processes.

Secondly, the main trading partners for South Africa are China, India, the United States of America (USA), and Germany, which, with the exception of India, are all entangled in geopolitical tensions. The USA and Germany are entangled in the Russia - Ukraine war and sanctioned by the G7 and the Western Countries as well as the European Union. A KPMG report argued that even more severe than the direct repercussions of the war for businesses that do business with and in Russia and Ukraine are the indirect repercussions that the war will have on Germany's overall economy (KPMG, 2022). Thus, some of the impacts on trade between emerging economies such as South Africa and key trading partners such as Germany were an increase in supply lead time and purchase prices that affected the economies of both countries (KPMG, 2022). Making this situation worse is the continued debate on the African Growth and Opportunity Act, commonly referred to as AGOA, which is a legislative measure that received approval from the United States Congress in May 2000. The African Growth and Opportunity Act (AGOA) grants duty-free

access to the United States market for more than 1,800 products to qualified nations in sub-Saharan Africa.

This is in addition to the more than 5,000 products that already qualify for duty-free access under the Generalised System of Preferences programme. Despite the recent summit to strengthen AGOA held in South Africa in November 2023, there are risks that might affect trade with the US. In recent months, some US Congress members have felt disappointed with South Africa because of its relationship with and stance on Russia, with suggestions that the US Congress should review the African Growth and Opportunity Act with South Africa (AGOA, 2024). This pressure is not expected to ease anytime soon; if anything, it is expected that more complications will ensue with the Israel-Palestine tension, where South Africa is entangled in an open case against Israel in the International Court of Justice, also known as the World Court, a strong ally of the Western Countries, especially USA, Britain and other European Countries.

The consequences of these geopolitical tensions among the world's powerful developed and emerging economies have resulted in uncertainty regarding the security of supply, problems with logistics and supply chains, reduced scientific and innovation collaboration, and rising logistics and goods costs. The manufacturing sector experienced heterogeneous cost increases during the pandemic, with industries like Coke and petroleum seeing the highest price hikes. These increases were driven by supply chain disruptions, contributing to rapid producer price inflation (PPI) (Santacreu & LaBelle, 2022).

Bednarski et al. (2023) acknowledged that there is an urgent need to understand how to manage interruptions in supply chains caused by ongoing geopolitical tensions. Escalating disruptions have prompted many businesses to completely re-evaluate the design of their global supply chains. These authors suggested that the effects of geopolitical disruptions on supply chains can be alleviated by (1) reconfiguring supply chains through regionalisation, back-shoring, and the abandonment of just-in-time delivery models, and (2) adopting emerging technologies, including blockchain, 3D printing, and artificial intelligence, to enhance supply chain transparency and facilitate modular manufacturing development.

3.2.1.2 Policy and regulatory uncertainty

McLean (2015) highlighted that policy uncertainty arises when economic agents harbour uncertainty associated with the economic consequences of government decisions that appear to lack clear and predictable outcomes. Baker et al. (2016) explained that it is crucial to acknowledge the significance of increasing levels of policy uncertainty, both on a global scale and within a national context. As a well-established connection exists between policy uncertainty and investment plans, this allowed the North-West University's School of Economics and the Business School in South Africa to develop a Policy Uncertainty Index (PUI) that assesses the impact of notable events within the country (Parsons & Krugell, 2022). The PUI is based on news coverage of policy uncertainty and its effect on the economy and data from the Bureau of Economic Research at the University of Stellenbosch regarding policy constraints on conducting business among manufacturers. An index figure of less than 50 reflects low uncertainty, while an index figure larger than 50 reflects high uncertainty and policy uncertainty based on the PUI has increased in South Africa to a new peak of 71.7 in the first quarter of 2023, up from 53.2 in the fourth quarter of 2017 (North-West University, 2023).

The sharp increase in the South African PUI during the first quarter of 2023 was due to the confluence of negative global and domestic variables that far outweighed the positive variables. In addition, factors such as constant power outages known as load-shedding, severe industrial action, sluggish economic growth, infrastructure bottlenecks, an increase in crime and corruption, and the "greylisting" of South Africa by the Financial Action Task Force all contributed to this high uncertainty (North-West University, 2023). In addition to economic, social, and administrative regulations, high levels of policy uncertainty directly impact businesses to drive multiple outcomes that boost or hinder innovation.

The Organisation for Cooperation and Development (OECD) regulatory reforms aim to boost innovation-friendly regulations (OECD, 2021). Thus, competition-enhancing changes in manufacturing and services have helped develop and spread innovative technologies. However, government regulations can limit the extent as to when and where a business can charge for goods and services. In addition, social regulations impact business practices. Thus, safety, health, and environmental regulations that are designed to protect the safety of the general public, society at large, and the environment have a

negative effect on the health, safety, and rights of both employees and consumers. A prime example of this was shown by the health and economic implications of COVID-19 regulations (Sun et al., 2022). In addition, governmental administrative regulation of both public and private sector operations provides possible areas for the control of taxes, corporate procedures, distribution networks, and intellectual property rights. Policy uncertainty can also have a positive effect on structural upgrading in manufacturing, pushing firms towards service transformation and vertical integration, especially in regions with advanced manufacturing structures such as China (Hu & Yan, 2021).

3.2.1.3 Cost of living-driven consumer behavioural change

Market competitiveness, expansion, and economic integration are ultimately fueled by consumers (Sánchez-Gutiérrez et al., 2019), and as a result of economic uncertainty, consumers undergo a transition in behaviour (Mehta et al., 2020). Such behaviour is driven by critical events such as pandemics and, in some developing countries such as South Africa, a worsening of the 'triple challenge' of unemployment, poverty, and inequality (Francis & Webster, 2019). The United Nation's International Labour Organization (2024a) has projected that the unemployment rate and the jobs gap have fallen below pre-pandemic levels.

The International Labour Organization (2024a) reported that in 2023, the worldwide unemployment rate was 5.1%, reflecting a modest (0.2%) improvement from 5.3% compared to 2022. In 2023, the worldwide jobs gap - defined as the number of individuals desiring employment, irrespective of their present availability or active search - decreased to 435 million, a reduction from nearly 500 million in 2020, 476 million in 2021, and over 440 million in 2022 (International Labour Organization, 2024a). Nonetheless, advancement was inconsistent. The labour force participation rate rose in high-income nations (+0.3%) and lower-middle-income countries (+1.5%), whilst it declined in low-income and upper-middle-income countries (by 0.1% and 0.3%, respectively). In affluent G20 nations, elevated inflation rates and increasing housing expenses have substantially diminished recent nominal wage increases (International Labour Organization (2024b). South Africa's unemployment remains very high, regressing from 25.2% official and 35.1% expanded from 2014 to 32.9% official and 41.1% expanded unemployment by the first quarter of 2024, respectively (Statistics South Africa, 2024) (Figure 3.2).

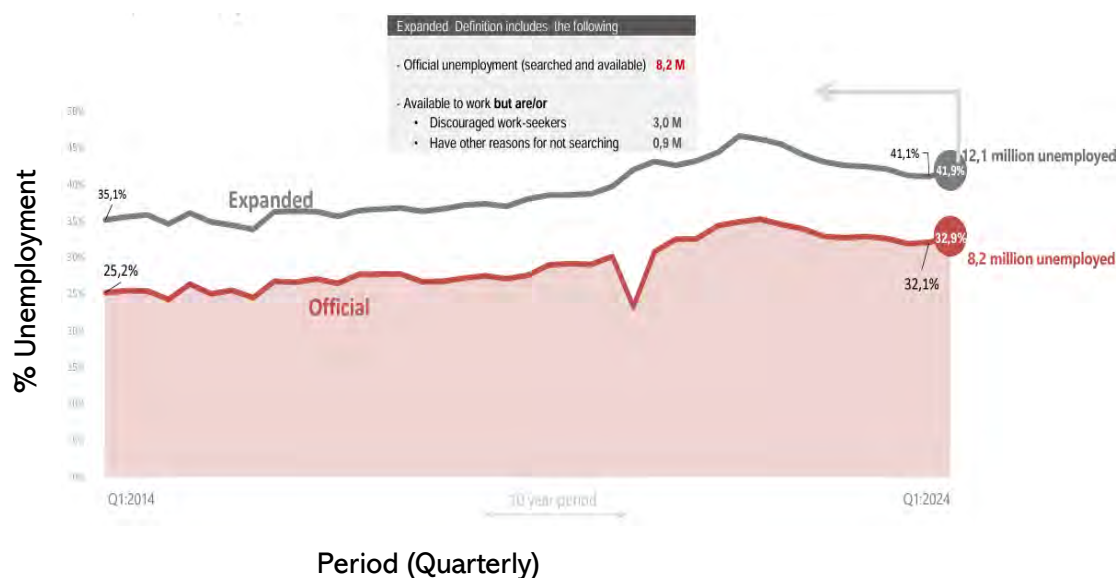


Figure 3.2: Unemployment rates in South Africa

Source: Statistics South Africa (2024).

Poverty also continues to be a challenge in South Africa and is closely linked to high unemployment rates (Ngubane et al., 2023). Inequalities are also worsened by rising food and energy prices, further exacerbated by an elevated risk of experiencing a debt crisis in 60% of developing countries and other low-income nations (International NGO Forum for Indonesian Development, 2022). Countries are suffering from a high inflation rate; this is also evident in European countries, which have recently increased inflation rates, resulting in a higher cost of living such that most European countries now have double-digit inflation, the worst in more than 30 years. The resulting complexity and economic pressure will impact firms in the foreseeable (Gössling et al., 2021). Some characteristics of human behaviour are challenging to predict when influenced by a crisis, which is when uncertainty becomes embedded in consumer behaviour.

Reduced current spending is the most common response to financial troubles, together with borrowing, especially from friends and family, and an increased use of credit to help people deal with a challenging financial situation. Individuals and families also resort to less expensive options for basic needs (Wiersma et al., 2020). The changing preferences are also evident in consumers from developing countries such as South Africa, who follow the global phenomenon (Abe & Mugobo, 2021). Consumers trade down by buying cheaper brands or privately labelled products over their favourite brands. Making the issue more complicated is that humans should be viewed as an inhomogeneous group of multiple categories of economic agents (Silinskas et al., 2021). Thus, depending on

factors such as age, life stage, socio-economic status, gender, and purchasing habits. People use diverse approaches to managing financial hardship. From a business perspective, this, unfortunately, increases operational uncertainty. Chen, (2024) explained that the changes in consumer purchasing behavior, such as the shift from planned to impulse buying, affect market supply and demand. These changes are also influenced by complex purchasing paths introduced by the digital era (Su et al., 2024), thereby compelling manufacturers to adapt production schedules and inventory management continuously to accommodate these fluctuations.

3.2.1.4 Pandemic turbulence

The coronavirus (COVID-19) pandemic has altered many lives and compelled countries, societies, businesses, and individuals to reconsider how they live and work (Bartik et al., 2020). There is growing literature on the disruption and impact that COVID-19 has had on firms, especially small businesses (Chhatwani et al., 2022; Belitski et al., 2022). The World Bank noted that the COVID-19 pandemic shocked the private sector and jeopardised recent developments aimed at poverty reduction and shared prosperity. The impact of the pandemic on enterprises and the elimination of existing production capacities might have substantial repercussions on the economic prospects of both developed and emerging economies.

These are both short-term and long-term repercussions, especially if the most productive firms are destroyed by restricted mobility, economic activity, high transaction costs, and potential cross-country commerce (Golubeva, 2021; Mtotywa & Mtotywa, 2022). Regardless of business size and country, this disruption has resulted in firms around the world reporting lower-than-normal turnover, temporary closure or trading interruptions, and a projected reduction in their workforce. Anakpo and Mishi (2021) highlighted that the pandemic had impacted industries in South Africa as well as firms in Africa. This effect was particularly evident in industries with weak fundamentals and reduced resilience to shocks. Sun et al. (2022) argued that the COVID-19 pandemic also significantly impacted current performance and overall firm performance in several nations. These negative impacts were exacerbated by inadequate workforce availability resulting from labour loss due to sickness, quarantine, or death. From a global perspective, imposed lockdowns and their operational consequences had a detrimental effect on economies and seriously harmed corporate sustainability. In addition to the COVID-19 pandemic, Monkeypox

(Ashish et al., 2022) and, more recently, the Langya Henipavirus (Uwishema et al., 2023) have emerged.

It is evident that pandemics, or at least epidemics, will continue to cause uncertainty in firms and businesses in general, particularly those with operational management that may be unprepared or without contingency plans. Kannan et al., (2023) posited that with the help of smart technology, Industry 4.0 may be controlled remotely, which is crucial in times of worldwide disturbances such as during the COVID-19 pandemic. Industry 4.0 and 5.0 technologies accelerate digital transformation and promote public safety, production management, and transportation management.

3.2.1.5 Energy stability and security

Three factors create uncertainty and business challenges in South Africa (Kock & Govender, 2021; Viljoen & Dube, 2023) and other countries such as Nigeria (Adeshina et al., 2024), Zimbabwe (Akpan et al., 2024) a potential solution to Zimbabwe's energy issues could be harnessed from the country's growing interest in renewable energy systems (RES) for use in industry. Energy security, reduced reliance on fossil fuels, and promotion of sustainable industrial growth could be achieved by tapping into the nation's abundant renewable resources, which include hydroelectric power, solar power, and wind power, among others. Potential benefits to the environment, grid reliability, and energy costs could accrue from the incorporation of RES. However, challenges like upfront costs, power grid integration issues, and the need for supportive legislation should be addressed. The use of RES could provide Zimbabwe with a future energy that is safer, more sustainable, and more cost-effective. Owing to the dearth of studies considering RES integration across the different sectors in Zimbabwe, hence, this presents the status and energy policy evolutions, a concise strength, weaknesses, opportunities and threats (SWOT) framework with outstanding challenges, and proposed solutions for sustainable energy development in Zimbabwe (Akpan et al., 2024), Bulgaria, and Romania (Murăraşu & Bujor, 2022) amongst others. These include constrained availability of energy due to geopolitical tensions and economic sanctions against Russia (Murăraşu & Bujor, 2022), energy shortages resulting from an unstable power supply grid, and a slow transition to renewable energy. The availability of a stable energy supply is closely linked to economic and industrial sustainability (Olanrewaju, 2019). South African manufacturing industries, particularly the basic iron and steel, petroleum, chemical and chemical-related products

and textile industries, have contributed to current industrialisation in the country and remain among the most energy-intensive industries (Kan et al., 2020). Dewa et al., (2020) explained that the unstable energy supply (loadshedding) had resulted in manufacturing sector experiencing production halts and increased downtime, which compromises delivery schedules and overall productivity. Mashapu and Mathaba (2024) reported that in some cases loadshedding has led to a substantial increase in operational costs, with businesses relying on diesel generators and thereby experiencing an up to 775% rise in energy expenses during outages. It is sometimes worse with small businesses which are particularly vulnerable, and which face significant financial losses and, in some cases, business closure due to their reliance on the national grid and limited access to alternative energy sources (Madumi, 2023).

This raises uncertainty within South Africa and other developing countries facing the challenge of energy security. Fortunately, the water, energy and food (WEF) nexus is experiencing a revolution associated with the Internet of Things and big data analytics (David et al., 2022). Despite the small but considerable program for renewable energy from utility-scale, grid-connected, independent power producers, coal-fired power plants still supply 90% of the electricity in South Africa (Baker & Phillips, 2019). A shift in the energy supply mix that is in line with international trends requires appropriate policies in BRICS countries due to their reliance on fossil fuels (Ndlovu & Inglesi-Lotz, 2019)

Most of the non-OECD countries' portion of the world's primary energy supply comes from China, India, and Russia, while most of South Africa's energy needs are met by coal, a fossil fuel that is inexpensive but whose combustion contributes to environmental damage. Novel power generation methods are needed in African countries to keep up with rising demand, particularly as developed European nations such as Germany face challenges with regard to energy security; therefore, their industrial sustainability is vulnerable in the short to medium term (Hearn et al., 2022). According to Bhagwan and Evans (2022), the energy sector now has more prospects for efficiency and innovation because of the technologies of the Fourth Industrial Revolution (Industry 4.0). Energy consumption intensity has decreased in several industrial sectors, such as cement manufacturing, due to the use of energy substitution strategies. Despite this, rising levels of energy consumption can be attributed to increased levels of industrial production in emerging economies, which is directly related to rising populations and economic growth

in these countries (Figueiredo et al., 2022) and geopolitical developments (Antonakakis et al., 2017).

3.2.1.6 Entrenchment power of large firms

Large firms use a multifaceted approach to entrenchment power, involving both internal mechanisms and external influences that reinforce their dominance. These include scalable resources absorbing new entrants' market share (Chu, 2014) and political influence, often shaping regulations and policies to their advantage (Zingales, 2017). The extent to which the government can effectively connect with "big businesses" is crucial to the country's economic growth, given the deep roots of the country's large established industrial firms (Lee et al., 2013). However, the interests of enormous corporations and the goals of international development are often at odds, particularly when large corporations use their dominant market position to their benefit by engaging in predatory pricing, limiting access to key suppliers, and otherwise engaging in unfair business practices (Gerber, 2016). In addition, large firms may be able to improve their manufacturing productivity and product quality for well-established items and technologies due to their economies of scale and financial advantages (Tayal et al., 2021). These firms also employ efficient and inefficient strategies (Rosenbaum, 1998), and market monopoly or oligopoly. Irrespective of efficient or inefficient strategies, large firms dominate through efficiency. In contrast, other firms maintain it through less efficient means, such as strategic acquisitions or market manipulation, which can slow down the market's ability to correct inefficiencies (Rosenbaum, 1998). Additionally, market power can distort prices and economic performance, negatively impacting innovation (Audretsch et al., 2023). As a result, large manufacturers set rules for the value chains in which they participate, dictating which firms can participate and the resulting effects (Reynolds, 2024). Overall, their actions and outlook are slanted against micro-, small- and medium-sized enterprises (Goga & Avenyo, 2022).

3.2.1.7 Skills for Future Industrial Work

An ageing workforce, technology-based skills required for future jobs, a disconnect between education and industry skills, and labour mobility all contribute to uncertainty related to skills requirements and availability for future work in the manufacturing industry. In general, demographic data indicate a tendency for the active labour force to age, which increases the need for age-friendly surroundings, long-term care and a more

highly skilled labour force. White et al. (2018) highlighted that changing demographics have a variety of consequences, such as behavioural differences between generations in the workplace and other workplace dynamics. According to research conducted at the University of Oxford, by the year 2025, the labour force will be reduced by approximately 47% (Frey & Osborne, 2016). This is a major threat to the financial security of the workforce in the future. In operationalising a sustainable future, the term "skill revolution emergency" describes the development of strategies for assisting the labour market in training workers for emerging jobs and advancing their existing expertise within the digital age (García-Pérez et al., 2021). A recent example of this is the June 2023 announcement by BMW of its investment of €200 million (approximately R3.8 billion) in the BMW hybrid car plant in South Africa and the focus on training staff for the production of electric vehicles. A significant gap exists between current workforce skills and the skills needed for future manufacturing environments. This mismatch creates uncertainty as firms struggle to find qualified personnel to meet the demands of advanced manufacturing processes (Penesis et al., 2017).

In addition, increased labour mobility contributes to the uncertainty of the availability of skills in firms. Cappelli et al. (2019) asserted that labour mobility is a significant factor in regional development, but this may not necessarily benefit local firms even though labour recruited from skills-related industries positively affects operations performance. At the business level, there is evidence that recruiting employees who have participated in innovation projects improves business performance, so labour mobility is crucial for transmitting knowledge between enterprises. In addition, globalisation and digitalisation have changed the workplace, and this requires a reorientation of skills for future work opportunities. Education is one of the areas most challenged by digitalisation, and this increases the urgency of adapting skills to 21st-century work market demands.

In short, Industry 4.0 requires job market survival conditions, particularly as the speed of disruptions in firms affects their productivity to further increase uncertainty (García-Pérez et al., 2021). Businesses should embrace the digital paradigm as much as their employees, as this has helped with virtual collaboration, computational thinking, internationalisation, and multidisciplinary teamwork. This, in turn, has assisted with market competition relative to redirected education to help students and employees acquire the necessary market and transversal abilities to complement their needs to drive

the teaching-learning process. In addition, now that Industry 4.0 is well underway, it will continue to rapidly alter the skills environment in numerous industries.

3.2.1.8 Generational work behaviour and ethics

Several generations are represented in the workforce today, and each of these generations brings a diverse and unique set of perspectives, values, work behaviours, and work ethics to the workplace (Olckers & Booysen, 2021). The multigenerational workforce now influences business outcomes (Singh & Chaurasia, 2022). With a retirement age of 60 to 65, most firms may have four generational cohorts in their employment, including Baby Boomers, who are employees born between 1946 and 1964; Generation Xers, who are personnel born between 1965 and 1980; those between 1981 and 1995, known as Generation Yers or Millennials; and some may be Generation Zers, born between 1997 and 2012 (Heyns & Kerr, 2018; Smeak, 2020). These generational cohorts are indicated in Figure 3.3.

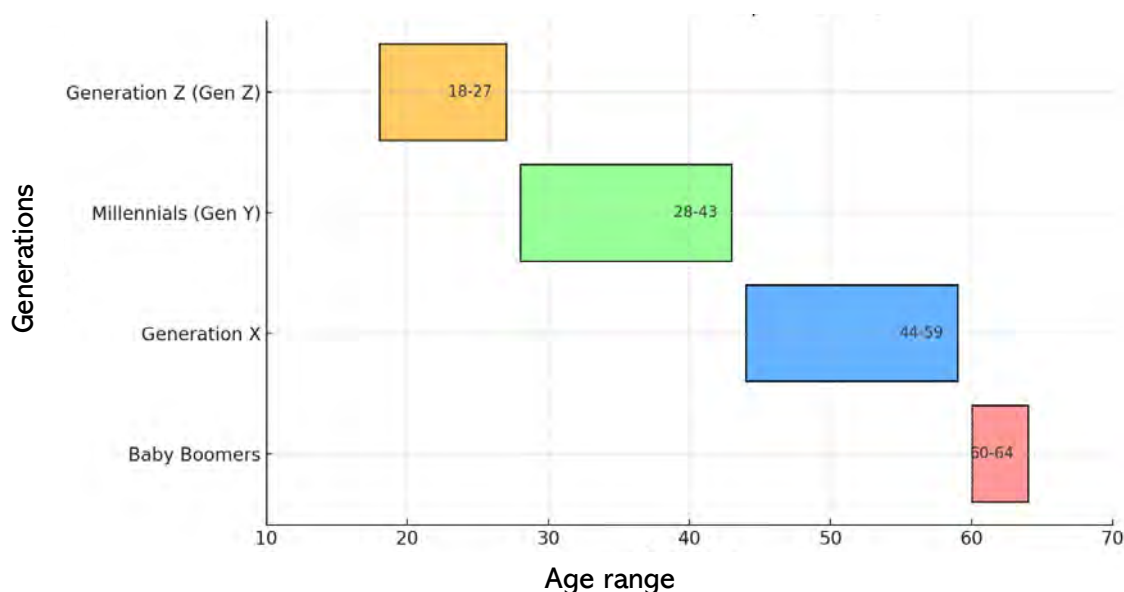


Figure 3.3: Generations in the workplace in 2024

Source: Author

A variety of human factors enter the workforce along with staff that span multiple generations, particularly younger generations, and these factors have a significant impact on the culture of a firm and the workplace. Younger employees have beliefs and objectives distinct from those of older employees, necessitating a deeper awareness of

their motivational drives in the workplace (Heyns & Kerr, 2018). As human capital is critical for the performance of a firm, an inadequate understanding of these dynamics creates challenges and brings uncertainty to the workplace, so it is essential to comprehend the factors that influence employee conduct at work (Singh & Chaurasia, 2022).

Intergenerational differences significantly affect workforce dynamics and organisational management, presenting both challenges and opportunities. These differences arise from distinct values, experiences, and attitudes shaped by unique historical, political, and social events for each generation. Manongcarang and Guimba (2024) posited that each generation exhibits distinct characteristics in technology usage, social values, and core values, influencing their communication preferences and work ethics. This is because generational differences manifest in communication styles and work values, leading to potential misunderstandings and conflicts if not managed properly (Fennelly & Perry, 2024). Generational differences can also contribute to skill mismatches within the workforce, which requires approaches that will enable customised training programs and regular skills assessments to bridge these gaps (Naliaka & Ngui, 2024). Despite these differences, if well managed, there are opportunities with diverse generations for firm development, innovation, and creativity. Appelbaum et al., (2022) highlighted that adapting various human resource tasks to generational disparities is also necessary for a firm to attract and retain talent. Socio-environmental issues such as the COVID-19 pandemic prompted a generational shift in how people feel about their careers and the future workforce. This shift has the potential to spark tensions between older and younger workers, and research studies have urged the need to manage conflicts caused by generational differences, suggesting that this is a complex issue that is influenced by multiple aspects within firms (Appelbaum et al., 2022). Nonetheless, studies have reported statistically significant differences and similarities between the various generational cohorts, mainly in terms of tenacity, hard work, and delayed gratification (Van Der Walt, 2016)

3.2.1.9 Process capability and variation

Uncertainty exists at every industry level, from detailed process descriptions to manufacturing at different sites. The adoption of process models is highly dependent on the capacity to manage system volatility. The seminal work on statistical process control

(SPC) was developed by Shewhart (1938) to monitor manufacturing processes, assess their inherent unpredictability and quality and highlight the existence of variation in any process. (Mrugalska & Wyrwicka, 2017) highlighted the vital need to comprehend the variation required to manage and enhance manufacturing processes effectively and emphasised genuine process as well as measurement variation. Here, actual process variation comprises common cause and special cause variations, whereas measurement variation comprises repeatability and reproducibility variation (Evans, 2017).

Variation attributable to a common cause is the random variation in stable processes, while special-cause variance is an unpredictability resulting from an external factor. The differences, particularly in special cause variation, can have a detrimental impact on the process capabilities, whereas the measurement variations impact product quality, on-time delivery and customer satisfaction (Evans, 2017). Such variation can be caused by various technological, methodological, human, and operating environment issues. The concept of a routine-based approach to capability development provides a connection between a firm's past actions and its competitive advantage. Reducing the unpredictability of process operations is influenced by social systems composed of individuals, their objectives, knowledge or skills, and work practices. The decrease is due to early (derived from core skills/competencies) firm activities that will positively impact process and product quality, cost, delivery reliability, and turn-around time (Katombe & Munapo, 2016). The interaction between these factors generates uncertainty and volatility in the business environment so that, due to the variety of patterns and events occurring across environmental sectors, firms are confronted with ambiguous situations that produce an even greater degree of uncertainty in the environment and pose latent dangers to their survival (Haque & Ali, 2016).

As indicated in Table 3.1, there is a research gap in studies of multipronged operational uncertainty constructs with respect to focus and operating levels, dimensionality, and management decision tools and applications.

Research Gap 1: Operational uncertainty dimensionality, management decision tools, and application

Generally, literature has considered uncertainty in operations by focusing on the process, product, or risk-related activities and functions. Specifically, the majority of the studies considered the external environment level. A literature review revealed that the policy

uncertainty index (Parsons & Krugell, 2022; Lolić et al., 2022) and the COVID-19 pandemic-induced index. Olubusoye et al. (2021) and Salisu et al., (2021) focused on a single type of uncertainty at an external environmental level. Noticeably, few recent studies were unidimensional (Mitnovitsky et al., 2015) or multi-dimensional (Vlasenkov et al., 2023), although they focused on the organisation rather than the external environment. Vlasenkov et al. (2023) investigated operational uncertainty in manufacturing as a multi-faceted issue that impacts various aspects of production, from financial performance to system reliability and human factors. This uncertainty arises from diverse sources, including fluctuating operational costs, unpredictable input conditions, and human factors, all of which can significantly affect manufacturing outcomes. Most studies have considered uncertainty in operation either at the external or organisational level, but they rarely considered it as a multi-dimensional construct at different operational levels (external environment, industry, organisational) (Table 3.1).

Table 3.1: Research gap from the published literature and potential for contribution

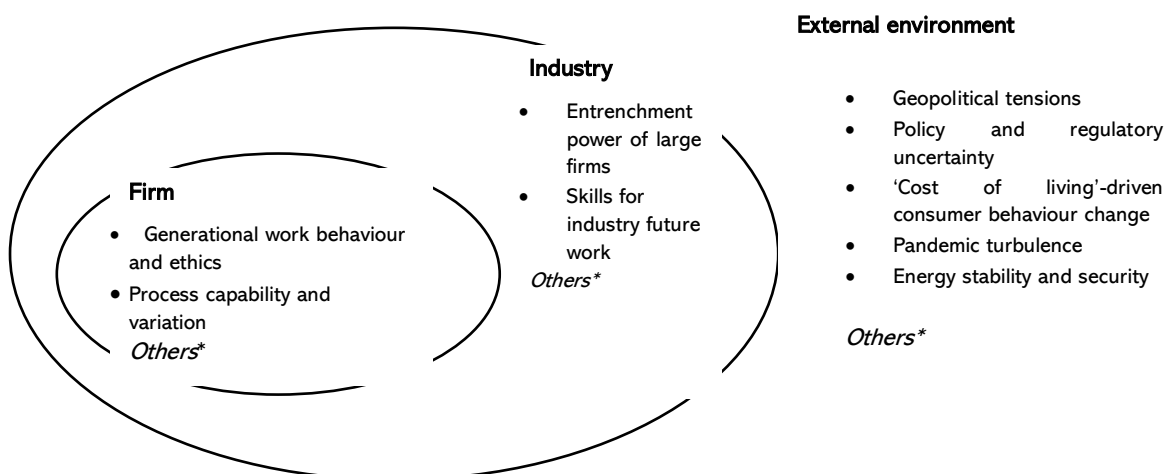
Author(s)	Operational Uncertainty Construct				
	Focus and Operational Level		Dimensionality	Management decision tool Application	
	Uncertainty in Operations/ risk, etc.	Firm and industry and environment		How much? Low/medium /high	Scenarios/ configurations/ MCDM*
(Hwang et al., 2020)	CD	NC	IM	NC	CD
Jagtap et al., (2023)	CD	NC	IM	NC	CD
Mitnovitsky, (2015)	CD	IM	IM	CD	IM
Sagawa and Nagano (2021)	CD	IM	IM	NC	CD
Sniazhko (2019)	CD	CD	CD	NC	NC
Salisu et al. (2023)	CD	IM	IM	IM	CD
Vlasenkov et al. (2023)	CD	IM	CD	CD	CD

CD: Considered; IM: Imperfect; NC: Not Considered; *Linked to optimum performance

Source: Author

Such single-type uncertainty confirms the assertions made by Sniazhko (2019), who highlighted challenges regarding research on operational uncertainty resulting from inconsistency in conceptualisation and measurement, limitation to single-type uncertainty and a minimised role of decision-makers in its management (Hopfe et al., 2013; Jagtap et al., 2023; Sniazhko, 2019). This necessitates research that comprehensively identifies potential sources of uncertainty within the external environment in addition to focusing on the industry and individual firm level (Sniazhko, 2019). In short, research to identify and effectively manage comprehensive potential sources of uncertainty (Ward & Chapman, 2003) requires the analysis of uncertainty as a multi-dimensional construct (McKelvie et al., 2011; Sicotte & Bourgault, 2008)

The present research advances work related to operational uncertainty. The novelty and contribution of this research is that it identifies nine critical sources of operational uncertainty and does so at different levels of operations (the external environment, industry, and firm). This requires the analysis of uncertainty as a multi-dimensional construct (McKelvie et al., 2011; Sicotte & Bourgault, 2008). Guided by this principle, the nine sources of operational uncertainty within the external environment and at the industry and firm levels that negatively impact efficient manufacturing operations are indicated in Figure 3.4.



*Others** - included as there are other possible sources of operational uncertainty.

Figure 3.4: Classification of sources of operational uncertainty

Source: Author

At the external environmental level, these sources of uncertainty include geopolitical tension (GPT), policy and regulatory uncertainty (PRU), the cost of living-driven consumer behavioural change (CLC), pandemic turbulence (PDT), and energy stability and security (ESS). At the industry level, these sources of uncertainty include skills for future industrial work (SFW) and the entrenchment power of large firms (EPL), while at the firm level, sources of uncertainty involve generational work behaviour and ethics (GWB) and process capability and variations (PCV). Based on the review and the gap, the first proposition of the study linked to objective 1 can be proposed as follows:

Proposition 1: Operational uncertainty is a multi-dimensional construct

In managing operational uncertainty, it is important to consider the prevailing levels, which can be determined by a quantification index. This is the other element of the operational uncertainty, which is a dearth of studies. An index serves as a structured tool that quantifies various aspects of operations, enabling firms to evaluate performance, identify areas for improvement, and ensure that operations are in sync with firm strategies (Abdul Hadi et al., 2022; Papin & Quellien, 2006). Indices serve as comprehensive tools that integrate multiple indicators into a single coherent framework (Wagenhals et al., 2014), allowing decision makers to evaluate complex scenarios more effectively (Hwang et al., 2020; Mozakka et al., 2024). This approach not only simplifies the decision-making process, but also ensures that decisions are informed by a holistic view of performance and strategic objectives (Chen & Yang, 2018). Indices are particularly valuable in contexts where multiple variables must be considered simultaneously, offering a composite measure that can guide operational decisions (Abou-Chakra (2021; Awang et al., 2022). There are three common types of indices, which are quantification, maturity, and readiness (Table 3.2).

These are the readiness index, maturity, and quantification indices. Pacchini et al., (2019) explained that readiness describes the ‘state in which an firm is ready to transform to accomplish a task or goal of a phenomenon, while maturity index “can be used to find out the ‘as-it-is’ state of a firm on the path of transformation” (Wagire et al., 2021, p.605). The quantification index provides information on the intensity or variability of the phenomenon. The focus for the readiness index is predictive with the lens of future potential, while for maturity, the focus is on the evaluative or developmental stages and descriptive focusing on the magnitude or variability for quantification index. The time

orientation being future focused for readiness while present relative to the continuum and present for maturity and quantification index, respectively.

The nature of the measurement is potential and capability for the readiness index, while levels or stages for the maturity index and numeric quantification for the quantification index. Index aggregation methods can be either additive or geometric and applicable in different phenomena (Gan et al., 2017). The output is generally 0 -1 or percentage of readiness (Awang et al., 2022; Pacchini et al. (2019) and quantification index (Abou-Chakra, 2021; Gandhi & Thanki, 2024), while its generally maturity levels or stage for the maturity index (Moura & Kohl, 2020; Nenadál et al., 2022). These three types of indices are interrelated, though unique, and measure particular contexts.

Table 3.2 Type of indices

Aspect	Readiness Index	Maturity Index	Quantification Index
Purpose	Assess preparedness for future goals	Assess the developmental stage (progress)	Measure the intensity or variability of a phenomenon
Focus	Predictive (future potential)	Evaluative (developmental stages)	Descriptive (magnitude or variability)
Time Orientation	Future-focused	Present (relative to a continuum)	Present
Key Question	"How prepared is the system?"	"How developed is the system?"	"How much variability or intensity exists?"
Nature of Measurement	Potential and capability	Levels or stages	Numeric quantification
Aggregation Method	Weighted average or geometric mean	Summative or weighted scoring	Arithmetic or geometric mean
Output	Readiness score (e.g., 0–1, or percentages)	Maturity level (e.g., stages or scores)	Numerical value (e.g., 0–1, or percentages)

Source: Author

Developing this index is crucial in operations management, as it provides a systematic and simplified approach to assess, compare, and manage complex data sets. It is also an essential tool for decision making, allowing stakeholders to assess performance and enhance continuous improvement efforts by providing a quantitative measure to assess operational uncertainty. As such, the first methodological gap.

Methodological Gap 1: Quantification index for systematic and simplified approach to assess, compare, and manage operational uncertainty complex data for decision making

Courtney (2001), supported by Walker et al. (2003), promoted the classification of the levels of uncertainty as this helps with decision-making. The overall levels of operational uncertainty are classified as either clear enough future or predictable outcomes, alternative futures, range of futures, and true ambiguity (Courtney, 2001; Millet & Wedley, 2002; Walker et al., 2003). These are indicated in Table 3.3. This classification must be grounded in identifying and effectively managing comprehensive potential sources of uncertainty (Ward & Chapman, 2003; McKelvie et al., 2011; Sicotte & Bourgault, 2008).

The operational uncertainty can differ in levels, as not all of them have the same level in the manufacturing firm. In addition, the uncertainty levels in manufacturing are high. As such, the second proposition is formulated as follows:

Proposition 2: Operational uncertainty is a norm in the manufacturing sector, as not all relevant information is already known to decision-makers

Table 3.3: Level of operational uncertainty

Uncertainty levels	Decision-making during the operational uncertainty
Predictable outcomes	The range of future possibilities is unlikely to significantly affect this decision. A deterministic problem is one in which the decision-maker can safely assume that all relevant information is already known.
Alternative futures	The decision's outcome is contingent on a set of distinct alternative futures. The likelihood of each possible outcome occurring is likewise known with some precision. Managers can think through every conceivable future and how their decisions will play out in each of them. It is feasible to identify a set of future outcomes that is both mutually exclusive and exhaustive.
Range of Future	Due to the complexity of the variables at play, it is not possible to divide these futures into a discrete and exhaustive set of possibilities; yet, there are additional alternative futures that are crucial to the decision. In addition, the mechanisms that will bring about certain future conditions cannot be simply specified, making it impossible to calculate the precise probability of future events.

Uncertainty levels	Decision-making during the operational uncertainty
Highly uncertainty (true ambiguity)	It is impossible to predict or even imagine the possible futures that matter when there are too many possibilities and insufficient known information to narrow them down. While the range of potential outcomes and the likelihood of certain occurrences can be defined, neither can be determined with certainty. Planning decisions at this level of ambiguity is exceedingly challenging, and it may be preferable to wait for the situation to settle itself toward better-defined conditions.

Sources: Developed by Courtney (2001) on levels of uncertainty and Walker et al. (2003) from decision-making levels.

3.3 Impact of operational uncertainty in operations

Operational uncertainty dimensions, individually or collectively, result in several operational challenges that negatively impact manufacturing operations. These include supply chain disruption, increased operational costs, market access restrictions, fluctuation of currency value, change in demand for goods, changes in labour availability and productivity, variation in product quality, and inconsistency in knowledge management (Figure 3.5).

Supply chain disruption. Geopolitical tensions disrupt trade flows and logistics operations, threatening the stability of global supply chains (Paché, 2024). Political instability, such as the Israeli-Palestinian conflict, causes transport disruptions and affects regional supply chains, posing challenges to global supply chain reliability. In addition to geopolitical challenges, there are other challenges associated with policy and regulatory uncertainty. This, policy uncertainty can also lead to supply chain disruptions by causing shifts in supplier bases and production locations, as firms respond to changing trade policies and economic conditions (Charoenwong et al., 2023). The COVID-19 pandemic also highly impacted global supply chains (Kumar et al., 2019), including industries in South Africa as well as the wider African continent (Anakpo & Mishi, 2021).

Increased operational costs. The need for new safety protocols and logistics adaptations regarding the COVID-19 pandemic caused severe disruptions in supply chains, affecting the availability of raw materials and spare parts, leading to delays in manufacturing and increased operational costs (Ghani et al., 2024). In addition, adjustments in supply bases due to geopolitical tensions lead to increased complexity of the supply base, which can increase operational costs for firms (Charpin & Cousineau, 2024).

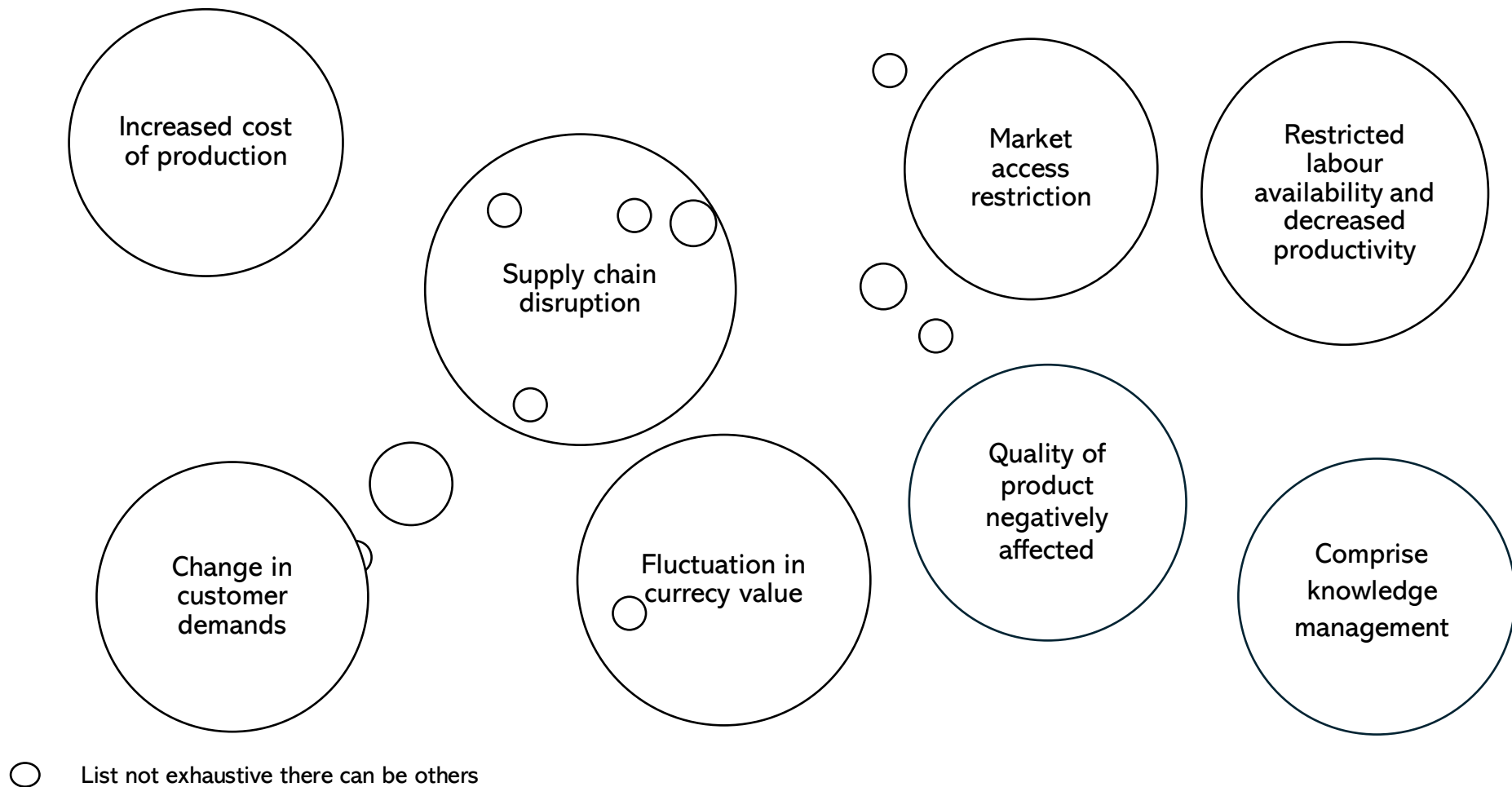


Figure 3.5: Classification of sources of operational uncertainty

Source: Author

This is due to the need for flexible and adaptive management strategies to navigate geopolitical risks (Rasshyvalov et al., 2024). Additionally, regulatory changes can restrict market access, forcing firms to adapt their supply chain networks to comply with new regulations or face penalties (Charoenwong et al., 2023). The global supply chains, characterised by fine-sliced, multi-tier structures, face increased complexity and reduced transparency, which can lead to market access restrictions. These challenges are compounded by currency fluctuations that affect the cost and availability of goods across borders. High levels of energy security incur additional costs with the need for secure power generation resources. Inflation and geopolitical risks further increase operational costs, affecting economic stability (Banna et al., 2023).

Market access restrictions. Geopolitical risks, including international conflicts and economic sanctions, restrict market access, complicate trade, and affect global transport networks (Rasshyvalov et al., 2024). In response, firms reduce their supply bases in countries with heightened geopolitical tensions, limiting their market access, and increasing dependence on fewer suppliers (Charpin & Cousineau, 2024). Furthermore, COVID-19 led to market access restrictions due to border closures and trade measures, affecting international trade and causing fluctuations in currency values (Aloqab et al., 2024).

Fluctuation of the currency value. Energy price volatility contributes to currency fluctuations, affecting countries' economic stability and trade balances (Li et al., 2022). Geopolitical tensions contribute to financial market volatility, affecting currency values and adding uncertainty to global supply chain management.

Change in demand for goods. Fluctuations in supply and demand are observed as consumer lifestyles change, affecting the quality and availability of products (Ghani et al., 2024). Thus, SMEs in particular had to innovate and reform to maintain operations and meet changing demands, highlighting the importance of modern strategies in navigating economic uncertainties (Ge & Wang, 2023). Consumer panic buying, often triggered by perceived shortages, can lead to sudden spikes in demand, causing supply chain disruptions. This influenced raw material and labour, leading to increased operational costs as they attempted to meet unexpected demand surges.

Changes in labour availability and productivity and variation in product quality are also influenced by the dimensions of operational uncertainty. The pandemic affected the

availability of the labour market, necessitating the implementation of safety measures to protect workers, which in turn increased operational costs (Ghani et al., 2024). These negative impacts were exacerbated by inadequate availability of workforce, resulting from labour loss due to sickness, quarantine, or death (Dhakal et al., 2021). Process capability directly affects product quality, as it measures the ability to produce items within specified limits. Fluctuations in demand can be better managed by ensuring a more stable process capability, which allows for flexible and responsive production systems. Furthermore, disruptions in energy supply can impact production processes, potentially affecting product quality and consistency. Industry 4.0 demands a workforce proficient in data analytics and automation to improve supply chain agility and resilience, reducing disruptions and operational costs (Adebayo et al., 2024; Holmes, 2024). Thus, investment in digital supply chain technologies, such as AI and ML, is crucial for access to real-time data and decision-making, which helps mitigate disruptions and optimise costs (Holmes, 2024). Knowledge management practices must adapt to generational preferences for technology and collaboration, ensuring effective transfer and utilisation of knowledge across age groups. Variations in process capability can increase operational costs due to inefficiencies and the need for rework or adjustments. Maintaining consistent process capability is essential for meeting market access requirements and avoiding restrictions due to noncompliance with quality standards (Mohammed, 2000).

Inconsistency and compromised knowledge management. Effective knowledge management is crucial in navigating these disruptions, as it enables firms to implement risk and disruption management strategies to mitigate the impact of changes in consumer behaviour. It is necessary to understand and control process variations, thereby improving supply chain performance (Munikhah & Ramdhani, 2022). As already mentioned, this labour is compromised by operational impacts such as pandemics. These impacts are related and overlap. As such, they cannot be looked at in a narrow, boxed manner, as operational uncertainty dimensions can affect multiple aspects in operations, or one risks having a domino effect on the others. A firm can minimise the impact of this uncertainty by reducing or coping with the uncertainty by using Industry 4.0 and 5.0 technologies and by developing configurations that ensure sustainable performance in the firm.

3.4 Industry 4.0 and 5.0 technologies

3.4.1 Progression of the Industrial Revolution – manufacturing lenses

The Industrial Revolution is a complex set of changes in the economy, technology, and society that has happened over a long time (Lojkine, 1986; Mohajan, 2021; Hahn, 2020; Mtotywa, 2022). The Industrial Revolution (IR) drove the transition from traditional methods of powering and managing work environments to more advanced and complex structures that align with contemporary development objectives to better serve societal needs (Groumpos, 2021). The world has seen the progression from the First Industrial Revolution (Industry 1.0) through to Industry 4.0, and we are now in the midst of Industry 5.0 (Akundi et al., 2022; Noble et al., 2022; Santhi & Muthuswamy, 2023). This is indicated in Figure 3.6, and a new debate has ensued, including the pathway of the Sixth Industrial Revolution (Industry 6.0) (Groumpos, 2021; Duggal et al., 2022).

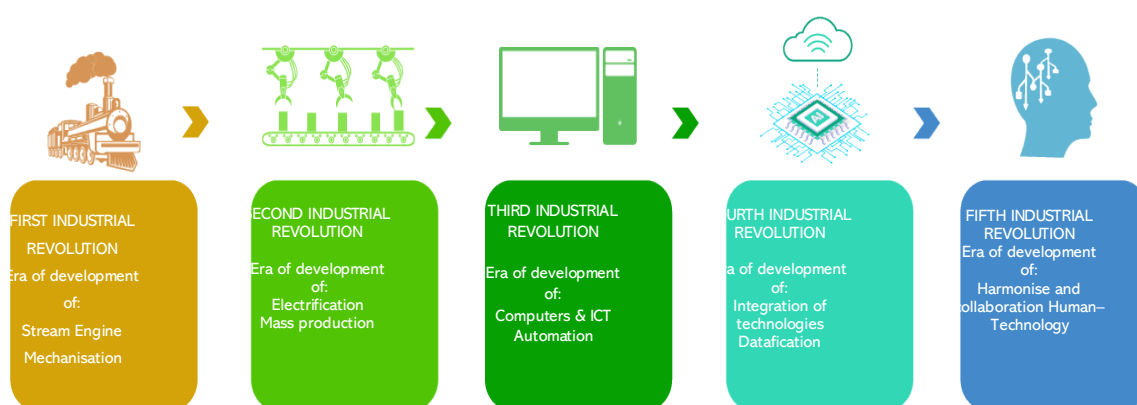


Figure 3.6: Progression of the Industrial Revolutions

Source: Author

In the first industrial revolution, we saw the development of steam engines and mechanisation (Mohajan, 2021). Industry 1.0 marked a significant shift from reliance on human and animal labour to the utilisation of machinery. This era witnessed advancements in chemical manufacturing and iron production techniques, as well as improvements in the efficiency of waterpower. Furthermore, Industry 1.0 saw a growing reliance on steam power and the emergence of machine tools. The iron and textile industries were significant players in this Industrial Revolution (Berrill & Ashton, 1949; Duggal et al., 2022). This was followed by the Second Industrial Revolution, which resulted in the development of electrification and mass production. During this time, iron was upgraded to steel, and coal was replaced by refined crude oil

as a primary energy source. Urban areas increasingly had their power supplied by electricity. Internal combustion engines eventually supplanted their steam-powered predecessors (Duggal et al., 2022). The Toyota manufacturing system introduced and standardised the manufacture of mass-market consumer goods using flexible scheduling and partial cross-training of employees (Duggal et al., 2022). Production structures such as cell manufacturing for modular part-wise manufacturing and the workshop were used for independent mechanical activities.

The Third Industrial Revolution resulted in the development of technology (Noble et al., 2022). The analogue process became digital, allowing it to be carried out by machines with much more accuracy, augmented by the introduction of automation (Groumpos, 2021). Multiple assembly bay portions were integrated, drastically reducing manufacturing times, and computerised assembly terminals were now available. With the introduction of operating systems, a new subset of software was required to run computers. In the following years, a brand-new market for this type of goods emerged to meet consumer demand. User information started to be in high demand due to the software revolution's emphasis on customisation (Duggal et al., 2022). Due to the magnitude and extent of these changes, the entire manufacturing, management, and government systems needed attention and to be revised (Schwab, 2017; Brito et al., 2017).

Industry 4.0 differs from the previous three industrial revolutions in that it features analysis using artificial intelligence developed to emulate analysis once only accessible to the human mind. Decisions are enhanced by digital algorithms, which can be significantly more accurate than human reasoning, resulting in improved human agility, intellect, and networking to influence how we work, live, and communicate with one another. Industry 4.0 is all about digitally connecting machines to make data flow smoothly and get the most out of them. Industry 4.0 capitalises on the exponential increase of digital capabilities, eroding the distinction between the physical and digital domains (Masters, 2021; Schwab, 2017; Xu et al., 2018;). Liao et al. (2018) found that the revolution led to significant developments in scientific knowledge, which led to individualised goods for consumers, streamlined manufacturing processes, and higher productivity.

We are now in the midst of Industry 5.0. In Industry 5.0, people and robots work together instead of against each other (Akundi et al., 2022). Industry 5.0 strives to increase the accuracy of machines with people's abilities. Additionally, during Industry 5.0, there was a push to make manufacturing more environmentally friendly, and they came up with ways to reuse and recycle materials (Aslam et al., 2020). There is also a need to reduce the damage that the manufacturing industry does to the environment. In supporting this view, Santhi and Muthuswamy (2023) explained that Industry 5.0 is supposed to bring humans back into the game so they can work together and add a human touch to products while focusing on sustainable manufacturing. Industry 5.0 is a new way of making things that focuses on how people and machines can work together (Enang et al., 2023).

Duggal et al. (2022) posited that there is also a trajectory toward the Sixth Industrial Revolution (Industry 6.0), suggesting that the prevalence of co-existing robots will become the prevailing standard within industrial settings. The probable result of past revolutions, which emphasised technical automation and personalised manufacturing, would be the emergence of monolithic production facilities. These facilities would involve machines connected to various task-specific artificial intelligence algorithms to produce goods based on consumer demands (Mithas et al., 2022). Industry 6.0 is anticipated to leverage various technologies to drive progress in multiple production domains and enhance the overall quality of life. New technologies are expected to shape further these revolutions that may arise in the future, and the technologies linked with each revolution will continue to develop and impact business and society.

3.4.2 Identified Industry 4.0 and 5.0 technologies

Table 3.4 presents the Fourth and Fifth Industrial Revolution technologies used in manufacturing. These are the Internet of Things (IoT) and enhanced connectivity, artificial intelligence (AI), big data, augmented and virtual reality (AR/VR), blockchain, advanced robotics and robotic systems, additive manufacturing (3D printing) and quantum computing.

Table 3.4: Fourth and Fifth Industrial Revolution Technologies

	Schwab (2017)	Xu et al. (2018)	Liao et al. (2018)	Koh (2019)	Ružarovský et al. (2021)	Ross and Maynard (2021)	David et al. (2022)	Bhagwan & Evans, (2022).	Raffik et al. (2024)	(Fazel et al., 2024)	Noble et al. (2022)
Internet of Things (IoT)	⊕	⊕	⊕	⊕	⊕	⊕		⊕	⊕	⊕	⊕
Enhanced connectivity									⊕		⊕
Artificial Intelligence (AI),	⊕	⊕		⊕	⊕	⊕	⊕	⊕	⊕	⊕	⊕
Big data analytics (BDA)	⊕		⊕	⊕	⊕		⊕	⊕		⊕	⊕
Augmented / Virtual Reality (ARVR)					⊕						⊕
Blockchain (BCC)				⊕							⊕
Autonomous Robots/ Robotic system (ARB)	⊕	⊕	⊕	⊕	⊕			⊕	⊕	⊕	⊕
Additive Manufacturing/ 3D printing	⊕	⊕	⊕	⊕	⊕						
Quantum Computing									⊕		⊕

Source: Author

3.4.2.1 Internet of Things and enhanced connectivity

The IoT encompasses physical objects equipped with sensors, software, and other technologies to enable connectivity and data exchange with other devices and systems (Kumar et al., 2019). The IoT is made possible by recent innovations in radio frequency identification (RFID), smart sensors, communication technologies, and Internet protocol standards (Ancarani et al., 2019; Gamede & Mtotywa, 2022). Enhanced connectivity is also developed, an Industry 5.0 technology that extends beyond the Internet of Things (IoT), encompassing a more comprehensive integration of various systems and technologies.

Automation is enhanced through IoT by integrating AI, which allows machines to perform tasks autonomously, reducing the need for human intervention and increasing production speed (Zaidi et al., 2024). The IoT systems collect vast amounts of data, which are processed to generate actionable insights. These insights support informed decision-making, improving operational efficiency and strategic planning (Shereef et al., 2024). The manufacturing industry is experiencing significant transformations due to technological advancements, particularly with the integration of Virtual Reality (VR) and the Industrial Internet of Things (IIoT) (Garg et al., 2022)

3.4.2.2 Artificial intelligence

Artificial intelligence can potentially enhance manufacturing efficiency, productivity, and sustainability (Badrinarayanan, 2024). Nevertheless, using artificial intelligence (AI) in the industrial sector gives rise to several obstacles, encompassing data collection and management concerns, human resource considerations, infrastructural limitations, associated security, trust, and the implementation process (Yahya et al., 2024). The manufacturing business is presently experiencing a paradigm shift driven by data, with the potential to revolutionise conventional manufacturing facilities into highly efficient smart manufacturing facilities (Badrinarayanan, 2024). The use of AI can assist manufacturing in promoting human-machine collaboration (Hartikainen et al., 2024). It can help with process optimisation and automation, quality control and inspection (Ghelani, 2024), and supply chain management. Thus, AI-powered human-machine interfaces improve the intuitiveness and precision of manufacturing operations, allowing for better collaboration between humans and machines (Hartikainen et al., 2024). Overall, AI enhances quality control through advanced computer vision and image recognition technologies, which are used for real-time product inspections and defect detection to

improve product quality and reduce waste (Badrinarayanan, 2024; Ghelani, 2024; Yahya et al., 2024). The integration of AI with the Internet of Things (IoT) facilitates real-time data analysis and decision-making, enhancing supply chain responsiveness and agility (Chaurasia, 2022).

3.4.2.3 Big data analytics

Using big data analytics (BDA) tools empowers firms to effectively handle and analyse extensive volumes of data to identify patterns, trends, and correlations (O'Donovan et al., 2015). This information has the potential to provide valuable insights into making strategic decisions, supply chain performance, improving operational efficiency, and enhancing customer satisfaction (Raj et al., 2024; Sahoo, 2022). Big data analytics has become a cornerstone in the manufacturing sector, especially with the advent of the Fourth and Fifth Industrial Revolutions. These revolutions emphasise the integration of advanced technologies such as IoT, AI, and cyber-physical systems to create smart, efficient, and sustainable manufacturing processes. Big data analytics facilitates this transformation by enabling real-time decision-making, predictive maintenance, and enhanced operational efficiency (Aprijal et al., 2024). The following sections explore the key applications of big data analytics in manufacturing within the context of Industry 4.0 and 5.0 technologies. Big data analytics is crucial for the integration of IoT in manufacturing, enabling the collection and analysis of vast amounts of data from connected devices (Hwang, 2024). This integration supports real-time monitoring and decision-making, enhancing the efficiency and responsiveness of manufacturing processes (Tawalbeh et al., 2024). Predictive maintenance is also significant application of big data analytics, allowing manufacturers to anticipate equipment failure and proactively schedule maintenance. This reduces downtime and maintenance costs while improving equipment lifespan (Aprijal et al., 2024).

3.4.2.4 Advanced robots – autonomous robots and robotic systems

Advanced Robots, or Autonomous Robots and Robotic Systems (ARB), can perform tasks autonomously or collaborate with humans. Automation in manufacturing, driven by robotics, improves product quality, reduces production cycle times, and increases overall productivity (Adebayo et al., 2024). Integration with AI enhances the efficiency of these robotics as AI tends to enhance sensory technologies, enabling complex recognition and high-accuracy task execution (Singh et al., 2024). This is because advanced sensing and

control technologies increase robotic intelligence, agility, and efficiency, making them more autonomous and effective in various industrial applications (Xie et al., 2024). During the COVID-19 pandemic, industries upgraded their production lines with automation tools to ensure continuous operations during the crisis (A. Chauhan, 2021). Despite this, there were also concerns about high initial costs, potential job displacement, and the need for regular updates and cybersecurity measures associated with advanced robotics. Noteworthy though, smart robots and systems are becoming increasingly common in supply chains and manufacturing shops. Smart manufacturing lets designers store the design files for things made in the cloud, which can be protected by strong access controls and used in many places (Adel, 2022).

3.4.2.5 Blockchain

Utilising blockchain technology (BCC) facilitates enhanced transparency and security in transactions and data management (Cao et al., 2024). Enhancing confidence and openness in supply chains, financial transactions, and contracts is paramount for decision-making processes. Blockchain technology is increasingly being recognised for its transformative potential in the manufacturing sector, particularly in the context of the Fourth and Fifth Industrial Revolutions. These revolutions emphasise the integration of advanced technologies such as the Internet of Things (IoT), artificial intelligence, and cyber-physical systems to create smart, efficient, and sustainable manufacturing processes (Marpina et al., 2024). Blockchain's decentralised and secure nature offers several key applications that align with these technological advancements, enhancing transparency, efficiency, and sustainability in manufacturing operations. Blockchain technology is increasingly recognised for its transformative potential in manufacturing. The blockchain facilitates supplier verification, parts tracking, and inventory management, reducing delays and enhancing operational efficiency in the automobile manufacturing process. It also provides the necessary transparency and security in industrial supply chains, boosting consumer confidence in product authenticity and quality. This capability allows stakeholders to track materials and goods with unprecedented detail, improving accountability and reducing errors in the supply chain (Bafna et al., 2024; Marpina et al., 2024).

3.4.2.6 Augmented and virtual reality

The utilisation of Augmented Reality (AR) and Virtual Reality (VR) technology denoted as ARVR offers immersive experiences and simulations that have the potential to enhance training, facilitate design evaluation, and enable remote inspections (Adhershini et al., 2024; Boardman et al., 2020). Bottani and Vignali (2019) highlighted that AR is a collection of technologies that enable the integration of computer-generated features or objects into the perception of the real-world environment. AR-mediated reality involves the enhancement of visual perception of the physical, real-world environment through the utilisation of computing equipment, while VR is the collection of technologies enabling users to engage with a computer-generated environment through interactive means (Akbari et al., 2022; Rueda et al., 2023). They exert an impact on decisions pertaining to product design and maintenance protocols. Thus, AR and VR facilitate immersive design and prototyping, allowing manufacturers to visualise and modify designs in a virtual environment before physical production. This reduces the time and cost associated with traditional prototyping methods; (Garg et al., 2022). Virtual manufacturing platforms enable collaborative design processes, where stakeholders can interact with 3D models in real time, enhancing decision-making and reducing errors (Soori et al., 2024).

3.4.2.7 Additive manufacturing (3D printing)

Additive manufacturing (3D printing) (ADM) is needed to make things more personalised and reduce waste and resource use. Additive manufacturing allows for the quick production of prototypes, enabling faster design iterations and reducing time-to-market for new products (Dubey et al., 2024). This capability is crucial for industries such as automotive and aerospace, where design precision and innovation are paramount (Jayakrishna et al., 2023). Öberg (2023) posited that 3D printing promotes rapid prototypes and extensive customisation, allowing for the production of tailored products to meet specific consumer needs. In the context of Industry 5.0, additive manufacturing supports human-machine collaboration, enhancing the design and production processes through intelligent systems. This integration allows for more interactive and personalised manufacturing experiences.

3.4.2.8 Quantum computing

Quantum computing (QCP) involves utilising quantum-mechanical processes to perform computational tasks at remarkably accelerated rates. Schröder et al., (2024) posited that quantum computing can significantly speed up and increase the accuracy of manufacturing simulations. This is important for problem-solving and continuous improvement in manufacturing. It offers the potential to solve complex logistical challenges in supply chain management, contributing to more sustainable and efficient industrial processes. This is particularly important as industry moves towards environmentally responsible methods (Singh et al., 2024). In addition, it can be integrated with IoT to transform manufacturing by enabling real-time data collection and advanced analytics. This synergy supports smart manufacturing, industrial automation, and predictive maintenance, leading to optimised supply chains and improved quality control (Sonavane & Aylani, 2024). Narwane et al., (2023) argued that quantum machine learning (QML) is emerging as a critical component in smart manufacturing, with applications in quantum neural networks, regression, and clustering. Additionally, this Industry 5.0 technology can be applied for the benefit of human workers and their well-being (Brahmi et al., 2022). Quantum computing utilises the fundamental principles of quantum mechanics to enhance computational capabilities, enabling the resolution of specific problems that are now beyond the reach of classical (Nofer et al., 2023).

Accelerating the creation and accumulation of firm-level technological capabilities is necessary for digital transformation and is an essential precondition for developing countries to leverage the capabilities of Industry 4.0 and 5.0 (Peerally et al., 2022).

3.4.3 Criticism of and challenges to the Fourth Industrial Revolution and its associated technologies

There is criticism directed at the Fourth Industrial Revolution. Moll (2021) argued that in comparison to the prototypical First Industrial Revolution, Industry 4.0 is a myth. Citing Polanyi's ideas, Moll argues that the conventional view of what constitutes an industrial revolution is less about technologies and more about a period of change characterised by long-term socio-economic change at a basic or structural level. This view is not well canvassed at this stage, but, more importantly, the proposed study will focus on Industry 4.0 technologies to determine whether there is congruency between their existence and application, particularly in light of Moll not considering Artificial Intelligence technology.

Despite this, the popular view in the literature that relates to criticism or challenges of the Industry 4.0 technologies revolves around their implementation or the barriers to their implementation.

It is a misconception that Industry 4.0 technologies are too expensive, that Industry 4.0 will bring mass unemployment, that businesses must forsake revenues to achieve sustainability, and that Industry 4.0 is only for huge multinational firms derived from markets in developed countries. However, it is an undisputed reality that multiple barriers hinder the implementation of Industry 4.0 technologies in firms, especially in developing countries. There are difficulties that emerging nations face in implementing Industry 4.0 technologies, including inadequate infrastructure, lack of a trained and skilled labour force, and problems with scalability and funding (Afolabi & Siaminwe, 2023; Alshahrani, 2023). Other authors have also advanced other challenges, including increased inequality in the labour market, literacy and skills deficiency, net displacement of the workforce by technology-driven machines, poor digital culture, and ineffective government policies (Xu et al., 2018; Zervoudi, 2020).

3.4.4 Transitioning to smart factories and barriers

Smart factories leverage a range of technologies, including the Internet of Things (IoT), cyber-physical systems, and advanced robotics, to create interconnected and intelligent production environments. As such, smart factory technologies represent a transformative approach to manufacturing, characterised by the integration of advanced digital technologies to enhance efficiency, productivity, and adaptability. Wang et al., (2023) advanced smart manufacturing and emphasised the integration of key technologies such as big data processing, industrial connectivity, and advanced robotics to enhance production traceability and operational efficiency within factories using a manufacturing execution system. This technology also utilises edge and cloud computing to monitor real-time data. Industry 4.0 technologies such as IoT, AI, and Big Data transform operations management by enabling smart, data-driven decision-making and real-time monitoring systems (Garrido et al., 2024). Shahab et al. (2024) explained that the Internet of Things (IoT) enables seamless connectivity and data exchange within smart factories, allowing for real-time monitoring and control of manufacturing processes. These sensors and devices collect critical data, facilitating predictive maintenance and optimising supply chain operations. (Kumar et al., 2022) also support this view, positing

that IoT, together with cyber-physical networks, are important to creating "smart factories" that integrate linked processes and activities (Soori et al., 2023). Other technologies, such as advanced robotics and collaborative robotics (Industry 5.0 technologies), are employed to work alongside human operators, improving productivity and safety in manufacturing environments. These automation technologies streamline production processes to reduce errors and increase throughput (K.-L. Wang et al., 2023). The 2024 South African manufacturing report by PricewaterhouseCoopers (PwC) indicated that digital transformation is redefining the sector through Industry 4.0 technology. It further asserts that smart factory technologies enhance the importance of production efficiency and sustainability. These technologies are fundamental to the notion of Industry 4.0, which prioritises the digitalisation of production processes. This is particularly significant because smart technologies provide extensive automation, networking, and data-informed decision-making in manufacturing settings (Shahab et al., 2024; Kumar et al., 2022; Wang et al., 2023). While smart factory technologies offer significant advantages such as increased efficiency and reduced downtime, they also present challenges, including cybersecurity risks and the need for substantial investment in infrastructure and staff training (Sharma et al., 2024)

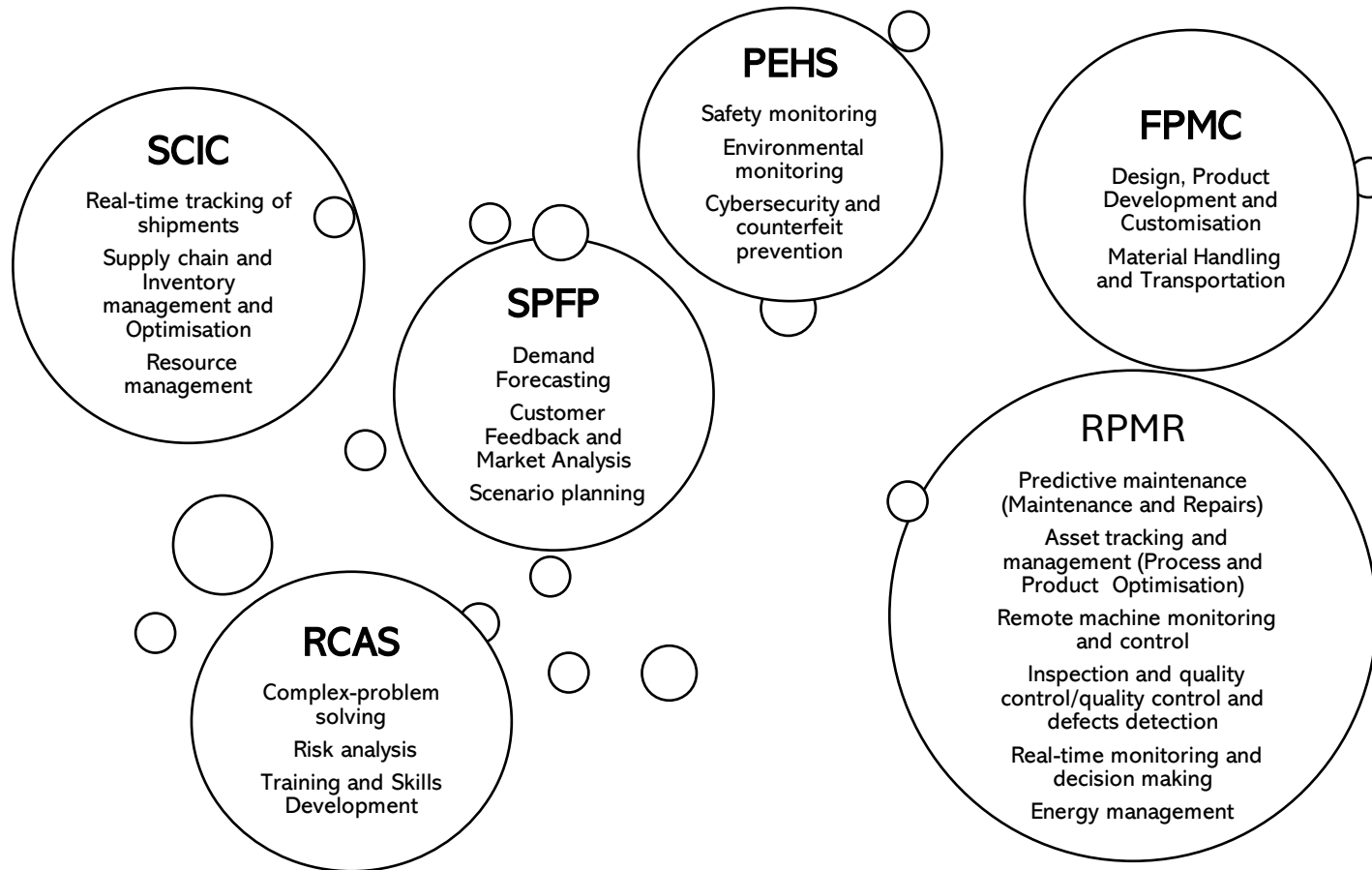
The challenges from cybersecurity risks emanate from its lack of security, its outdated nature, and its high vulnerability to attack (Mohammed et al., 2024). The other challenge is the attempt to secure the data, which can result in data manipulations affecting decision-making (Toussaint et al., 2024), or it can create problems for firms and result in business loss if the firm data lands in the wrong hands. Regarding the cost of investments, some technologies, such as advanced robotics, are very expensive and not easily implementable, especially for small and medium firms. Despite this, some technologies, such as AI and IoT, are deemed cost-effective and have a good return on investment. AI is regarded as one of the most effective technologies and is very effective in integrating with IoT, especially in resource-intensive operations, and helps optimise resource use and operational performance (Elegbeleye et al., 2024)

3.4.5 Deconstructing the capabilities of Industry 4.0 and 5.0 technologies

Capabilities refer to the amalgamation of various resources, skills, technologies, and processes that empower a firm to manufacture items efficiently, fulfil client requirements,

and maintain competitiveness within the market. Industry 4.0 and Industry 5.0 represent transformative phases in manufacturing, each characterised by capabilities to improve operational performance Choi et al. (2022). Industry 4.0 focuses on the integration of digital technologies such as IoT, AI, and robotics to create smart factories that improve productivity and efficiency. The use of IoT and AI to connect machines and systems enables real-time data processing and decision-making to improve productivity and reduce downtime (Rane et al., 2024; Raffik et al., 2024). It can also assist with predictive maintenance with AI technologies facilitating continuous monitoring and predictive maintenance, minimising system downtime and associated costs (Rane et al., 2024). It can also assist in supply chain optimization through enhanced data analytics to streamline supply networks, improving efficiency and product quality (Rane et al., 2024). Industry 5.0 emphasises human-machine collaboration, with the aim of combining human creativity with advanced technologies for more personalised and sustainable manufacturing solutions. It can help to focus on integrating human creativity with machine precision, using technologies like collaborative robots (cobots) (Kumar et al., 2022). Thus, it can enable sustainability and resilience to create more sustainable industrial ecosystems by addressing societal challenges such as environmental sustainability (Rane et al., 2024).

The analysis of eight Industry 4.0 and 5.0 – IoT, AI, BDA, BCC, ARB, ARVR, ADM, and QCP yielded 20 manufacturing capabilities, which were constituted into six themes or groups. These include (1) scenario planning and future prediction (SPFP), (2) supply chain integration and collaboration (SCIC), (3) flexible production and mass customisation (FPMC), (4) real-time system and process monitoring and response (RPMR), (5) root cause analysis and sustainable solutions (RCAS), and (6) protective ecosystem (humans and systems) (PEHS) (Figure 3.7).



○ List not exhaustive others are

Figure 3.7: Industry 4.0 and 5.0 technologies manufacturing capabilities

Source: Author

3.4.5.1 Scenario planning and future prediction (SPFP)

Scenario planning and future prediction (SPFP) effectively anticipate and adapt to unpredictable future circumstances, especially during operational uncertainty. Scenario planning entails the development of comprehensive and credible depictions of potential future outcomes (Cordova-Pozo & Rouwette, 2023). Industry 4.0 technologies offer advanced tools for the study, simulation, and visualisation of data, facilitating the development of increasingly complicated scenarios. This is facilitated by AI and ML, which make use of a wide range of computational techniques and algorithms that enable computer systems to perform tasks and make decisions (O'Donovan et al., 2015). These data may be used to predict maintenance requirements, customer behaviour patterns, and market trends (Krommuang & Suwunnamek, 2022). In addition, AI analysis of such data allows the identification of patterns and trends that may not be readily discernible to human observation. The IoT can also be utilised to observe patterns and construct scenarios grounded in factual performance and environmental information (Ahmetoglu et al., 2023). Together, these processes enable the generation of a holistic perspective on the present condition as well as prospective future scenarios. These technological advancements facilitate the implementation of scenario planning that is characterised by increased dynamism, enhanced level of detail, and reliance on data-driven approaches. In summary, complex systems can be effectively modelled with Industry 4.0 and 5.0 technologies (Ranthi & Muthuswamy, 2023), and various potential outcomes can be predicted, providing valuable insights for strategic decision-making (Noble et al., 2022). As the evolution of these technologies progresses, their significance in the realm of scenario planning is expected to expand, thereby empowering organisations to enhance their ability to predict and proactively address forthcoming difficulties and opportunities.

3.4.5.2 Supply chain integration and collaboration (SCIC)

Changing needs, rerouting, significant disruptions and compliance difficulties are only some of the many sources of ongoing disruptions in the supply chain (Teniwut & Hasyim, 2021; Unhelkar et al., 2022). Therefore, supply chains necessitate scrutiny and constant fine-tuning (Koh et al., 2019). The integration of supply chain management and collaboration (SCIC) with Industry 4.0 technologies augments connectivity, transparency, and efficiency throughout the entirety of the supply chain network. The integration of various systems and processes can lead to enhanced efficiency, cost reduction, heightened transparency, and improved customer service (Koh et al., 2019). Integrating

data from diverse sources is critical to generating insights and informing decision-making, as well as implementing advanced collaboration platforms to enhance communication and coordination among various stakeholders (Ajayi & Laseinde, 2023). Assisting in this regard, IoT devices enable the monitoring of items over the entire supply chain, hence offering real-time information pertaining to real-time data on location, condition, and delivery times. Radio Frequency Identification (RFID) and big data are useful technologies for supply chain optimisation, as RFID technology plays a crucial role in the digitalisation of supply chains by facilitating information analysis for automation and optimisation with sensor data (Konecka & Maryniak, 2020). The application of AI can be employed to facilitate demand forecasting, optimise inventory management, and offer valuable insights into the performance of supply chains. Additionally, the integration of blockchain technology can enhance record-keeping practices by ensuring security, transparency, and immutability. This is particularly advantageous in tracking the origin and history of goods and the implementation of smart contracts. Through the integration of various technologies, firms have the potential to establish a supply chain that exhibits efficiency and resilience (Fanoro et al., 2021) while also possessing the ability to anticipate challenges, adjust to fluctuations, and proactively meet market demands (Ajayi & Laseinde, 2023).

3.4.5.3 Flexible production and mass customisation

Manufacturing firms must respond effectively to dynamic market conditions and operational uncertainties with flexible production and mass customisation (FPMC) (Höse et al., 2023). Industry 4.0 technologies create personalised relationships with customers, optimise production chains, and make businesses more efficient (Liao et al., 2018; Schwab, 2017). Such technologies revolutionise automated manufacturing, asset management, and other industries by collecting, transferring, analysing, and storing data (Javaid et al., 2021). Likewise, IoT plays a significant role in manufacturing by facilitating the connection of objects through networks and enabling remote control of existing network infrastructure. Overall, integrating manufacturing processes with computer-based systems improves production efficiency and product accuracy while minimising the need for human intervention (Garg et al., 2022).

The IoT framework has a distinct component, the Industrial Internet of Things (IIoT), that is particularly useful in industry (Ali et al., 2023; Flores-García et al., 2023) such devices

encompass a range of technological components, such as sensors deployed on factory floors, real-time location systems utilised in logistical operations, and smart meters employed for efficient energy management (Flores-García et al., 2023; Peter et al., 2023). Despite being in its early stages of development, IoT technology has the potential to significantly enhance the value of businesses through the utilisation of powerful analytical tools to process data (Ahmetoglu et al., 2023; Kalsoom et al., 2021; Krommuang & Suwunnamek, 2022).

Artificial intelligence inside the industrial sector is recognised as a separate process from the digitisation and integration of information technology. The latter can be regarded as a necessary condition for the former, wherein digitisation and information technology serve as the foundational framework for executing AI/ML-based solutions (Plathottam et al., 2023). The full potential of IoT is realised when interconnected sensors effectively communicate with one another, facilitating the seamless exchange of data and knowledge (Ahmetoglu et al., 2023; Gamede & Mtotywa, 2022). This exchange occurs without encountering technological obstacles, ultimately transforming knowledge into tangible benefits on the business front, creating value, and enhancing efficiency in manufacturing.

3.4.5.4 Real-time system and process monitoring and response

Firms generate manufacturing information by utilising real-time data to provide precise and prompt decision-making processes that can yield beneficial outcomes for the entire business (Kang, 2022). This is through a real-time system and process monitoring and response (RPMR) approach. To achieve these efficiencies, it is imperative to integrate emerging technologies (Kühl et al., 2022). This integration enables the measurement and monitoring of real-time data from various points within the manufacturing process, ultimately leading to an unparalleled increase in data creation for decision-making (Nouinou et al., 2023).

It is imperative for manufacturing facilities to effectively handle the challenges posed by the exponential growth in data generation while also possessing the requisite analytical methodologies to get valuable insights from these extensive datasets. To effectively address the requirements of smart manufacturing, businesses must possess the capability to effectively utilise big data technology (O'Donovan et al., 2015). The utilisation of AI and machine learning (ML) algorithms enables the analysis of data and the generation of prediction models, automated decision-making processes, resource allocation

optimisation, and enhanced fraud detection (Kühl et al., 2022). Thus, AI and ML have capabilities to enhance cost-effectiveness, operational efficiency, and productivity advancements across various domains.

These applications encompass various functionalities, such as predictive maintenance, quality assurance, energy forecasting, safety and security, generative design, and experimentation. Predictive maintenance aims to enhance the real-time monitoring of equipment performance, thereby minimising unforeseen failures (Plathottam et al., 2023). Quality assurance facilitates the identification of product imperfections and aids in detecting errors on the factory floor. Energy forecasting contributes to sustainability efforts and assists in managing energy requirements.

3.4.5.5 Root cause analysis and sustainable solutions

Another capability of Industry 4.0 and 5.0 is for root cause analysis and sustainable solutions (RCAS). Identifying and resolving the root cause is a crucial step in the manufacturing process, as it is only through this process that manufacturing operations can be improved (Oliveira et al., 2023). Ito et al. (2022) posited that an improved root cause analysis supports the resilience of production systems. Notably, root cause analysis is time-consuming, particularly when dealing with a substantial volume of data pertaining to the manufacturing operation. The proliferation of automation and the emergence of Industry 4.0 has led to the expansion of sensorisation in manufacturing environments, resulting in a corresponding increase in available data (Laskurain-Iturbe et al., 2021). Quantum computing can fundamentally transform decision-making processes through its ability to solve complex issues and conduct simulations at velocities beyond traditional computers' capabilities. This technology possesses potential applications in optimisation, risk assessment, and scientific research. Quantum technologies is expected to significantly impact global industrial value creation in the foreseeable future. Additionally, the skill sets and competencies demanded of employees have transformed, leading to an increased need for relevant digital talent, especially in the context of root cause analysis and sustainable solutions. Additionally, traditional workplace boundaries have been dismantled, highlighting disparities in technology adoption and usage across different generations (Karaboğa, 2023). Industry 4.0 technologies can assist in aligning digital business strategies with talent management strategies (Husin et al., 2023). Augmented Reality (AR) and Virtual Reality (VR) can be used for different training experiences and

applications (Holuša et al., 2023; Xie et al., 2021). The utilisation of AR and VR technologies has brought about a significant transformation in educational methodologies by providing learners with immersive digital experiences, interactive environments, simulations, and enhanced engagement (Al-Ansi et al., 2023).

Collaborative tools, cloud computing, AI, and big data can all optimise knowledge management, which is a critical aspect of knowledge building. The utilisation of knowledge management (KM) to facilitate the acquisition of novel skills and capabilities among individuals presents substantiation that KM not only confers competitive advantages but also furnishes a mechanism for a firm's viability by enhancing fundamental capabilities or engendering new ones that can propel individuals in the era digital transformation (Anshari & Hamdan, 2022)

3.4.5.6 Protective ecosystem (human and systems)

The manufacturing and industrial processes involve a combination of human and system components that collaborate to ensure the safety of workers, maintain the operational integrity of systems, and safeguard the environment. This constitutes the protective ecosystem (humans and systems) (PEHS). Regarding operational integrity, there is an increased significance in the integration of cybersecurity and counterfeit protection within the framework of the protection ecosystem, which is evident in the context of Industry 4.0 and 5.0 technologies (Begum, 2024). As manufacturing firms increasingly integrate networked and intelligent systems, they expose themselves to heightened susceptibility to cyber threats and the accompanying hazards of counterfeit goods (Begum, 2024). These risks might potentially result in significant safety and operational consequences. In cybersecurity, this encompasses sophisticated techniques for identifying and mitigating potential threats, sometimes called advanced threat detection and response (Mohammed et al., 2024). The application of artificial intelligence (AI) and machine learning (ML) in the context of real-time surveillance and prompt reaction to potential cyber risks can guarantee the safeguarding of both Information Technology (IT) and Operational Technology (OT) networks. Utilising blockchain technology for secure transactions is an integral component of this framework. By leveraging blockchain's decentralised and immutable ledger system, manufacturing processes may establish a robust mechanism to safeguard transactions and communications, guaranteeing their integrity and traceability.

Robust access control measures encompassing biometrics, advanced encryption, and multi-factor authentication regulate access to critical systems and sensitive data.

An objective of the present study is to enhance the security of Cyber-Physical Systems (CPS) by implementing sophisticated cybersecurity methods to safeguard critical industrial systems and infrastructure. The organisation should prioritise employee training and awareness by implementing frequent training sessions to enhance employees' understanding of cybersecurity threats and best practices.

The successful incorporation of Industry 4.0 and 5.0 technologies necessitates the implementation of a strategic framework that safeguards against cyber risks and counterfeiting. The core focus of Industry 4.0 and Industry 5.0 lies in prioritising connectivity, intelligent systems, and sustainable practices. However, it is imperative to maintain a delicate equilibrium by implementing robust cybersecurity measures and effective strategies to combat counterfeiting. These measures are crucial for safeguarding the protection ecosystem within the manufacturing sector and extending beyond its boundaries. Manufacturing enterprises have the potential to leverage blockchain technology in order to enhance supply chain traceability (Zhou, 2024). Utilising blockchain technology to establish transparent supply chains facilitates the verification of product authenticity across the entire process, from production to final delivery (Salvankar, 2024).

Smart Packaging is a technological advancement in the packaging field that incorporates several intelligent features to enhance the functionality and efficiency of packaging materials. Implementing intelligent sensors, radio-frequency identification (RFID) tags, and quick response (QR) codes enables the verification of product authenticity using scanning mechanisms (Salvankar, 2024). Artificial intelligence (AI) has proven to be effective in the field of inspection and detection. Specifically, AI-powered image recognition and scanning systems have demonstrated their capability to identify counterfeit products. This is achieved by analysing patterns and abnormalities that could signify the presence of counterfeit items. The utilisation of digital twins is employed to mimic and validate the performance of products, thereby guaranteeing their adherence to the original specifications and thereby preventing counterfeiting (Chikwendu et al., 2025). Advanced analytics techniques are applied in anomaly detection, specifically in the analysis of sales and supply chain data (Chauhan, 2024). This approach aims to find

anomalies within the data that may indicate the potential existence of counterfeit goods within the market. Furthermore, the concept of the Internet of Things (IoT) may be used in the domain of Provenance, wherein IoT devices can be utilised to monitor and record the movement and the geographical whereabouts of various items. This implementation ensures the authenticity and traceability of those goods across the whole supply chain. Safety and security measures are implemented to mitigate cybersecurity risks and promptly identify and address unsafe practices.

Industry 4.0 and 5.0 technologies have created and will continue to create an innovative way to manage operations (Dallasega et al., 2018; Koh et al., 2019; Nsakanda, 2021; Noble et al., 2022). The capabilities of the technologies of Industry 4.0 and 5.0 are anticipated to foster flexibility and adaptation, enabling a dual role of reducing operational uncertainty and coping with its impacts (Naseem & Yang, 2021; Noble et al., 2022; Santhi & Muthuswamy, 2023). As a result, efforts are ongoing and need enhancement to guarantee that businesses can capitalise on the benefits of this transformation associated with Industry 4.0 and 5.0 technologies while managing inherent operational difficulties. This requires research as there is very little known about the combined impact and management of operational uncertainty on a firm's performance and the influence of Industry 4.0 and 5.0 technologies.

This analysis reveals that despite Industry 4.0 and 5.0's capabilities, there is a dearth of studies that leverage these capabilities.

Research Gap 2: Leveraging capabilities of Industry 4.0 and 5.0 to manage operational uncertainty

Based on the review and the gap, the third proposition of the study linked to objective 2 can be proposed as follows:

Proposition 3 :Industry 4.0 and 5.0 technologies capabilities can manage the operational uncertainty in the manufacturing sector.

3.5 Organisational learning

Having Industry 4.0 and 5.0 technology does not guarantee its use or effectiveness. Several factors contribute to this, with the study advancing that organisational learning is the potential signal that there is a probability of effective technology use in the firm.

Argote and Hora, (2017, p 579) explained organisational learning is a “processes of creating, retaining and transferring knowledge and has implications for the performance and competitiveness of organisations”. With the organisational learning firm modify their beliefs, attitudes, behaviours, and structures in reaction to environmental changes to guarantee long-term efficacy and survival. The efficacy of learning dictates the effectiveness of work and organisation. There are several factors that can influence the effectiveness of technological implementation. This included, among other inadequate knowledge and application, external pressure resulting in forced accelerations of implementation such as competition and survival (Sinha & Noble, 2008) and pandemic-induced changes (Lal et al., 2023; Patanjali & Bhatta, 2022) and sometimes technology overload (Rasool et al., 2022) These contribute to variations in the effectiveness of the firm's implemented technologies.

Progress in manufacturing has led to technologies for COVID-19-smart social distancing tags, the Internet of Things (IoT), artificial intelligence (AI) and autonomous robots (Sarfraz et al., 2021). There is a debate over the potential and risks of artificial intelligence and robots; a growing body of evidence demonstrates that these technologies have a bifurcating effect, deskilling or eliminating some jobs while raising the abilities and potential of others (Eaton & Heckscher, 2020). Thus, in many businesses, technology has reached a tipping point. The COVID-19 pandemic expedited and underlined certain components of that shift: factories run mostly by robots, dispersed workforces work online under close electronic surveillance, and a surge in collaborative tools that enable flexible teaming (Ardolino et al., 2022). Work from home accelerated the use of cloud technology and business communication applications such as Zoom, Microsoft Teams and Skype, enabling individuals to participate from home or in a different location (Lal et al., 2023; Patanjali & Bhatta, 2022).

A firm needs organisational learning to improve the effectiveness of Industry 4.0 and 5.0 technologies in improving business performance. The increasing prevalence of a digital presence is expected to contribute to the heightened occurrence of workplace monitoring and technostress concerns. Despite its importance, there is a paradoxical reality of Industry 4.0 technologies: a need for organisational learning for effectiveness due to sometimes inadequate knowledge and application in contrast to the need to accelerate the implementation of technologies in business. Tan and Olaore, 2022) posited that organisational learning has an all-encompassing effect on operations and employee

productivity to, thus, increase efficiency across the board, in all departments and at all levels of management. Basten and Haamann, (2018) suggested that with the help of organisational learning, firms may pool their employees' expertise to solve complex problems. However, organisations often fail to implement effective strategies due to the lack of specific guidelines. Tan and Olaore (2022) argued that firms may design tailored solutions that will facilitate the profound acquisition of information and sharing of that knowledge across all departments and divisions of the firm.

This underpins the importance of learning within firms to enhance and achieve their objectives. Firms that are more adept at learning are better positioned to capitalise on emerging opportunities and respond to emerging dangers, particularly those that require considerable organisational change. This strategic approach is crucial for effectively managing the inherent strengths and threats associated with Industry 4.0 (Ivaldi et al., 2022). The learning process involves utilising individuals' experience and practical knowledge as valuable assets for implementing, advancing, and incorporating innovative technologies. Thus, firms that are better able to develop new knowledge, innovate more successfully and adapt to changing environmental conditions more rapidly and efficiently obtain a competitive advantage over firms that are unable to do so. The achievement of sustainability in the context of Industry 4.0 is contingent upon a robust commitment to investing in the advancement of organisational learning. This process encompasses the dual aspects of knowledge exploration and exploitation.

In light of the inherent uncertainty that organisations must confront, the attainment of a favourable equilibrium between learning endeavours aimed at maximising the utilisation of existing knowledge (exploitation) and the allocation of resources towards the creation of novel knowledge (exploration), is closely tied to the organisational climate and cultural backing for fostering an appropriate and conducive learning environment (Hardy et al., 2019). Adopting a novel perspective when conceptualising organisations, management, and change is imperative to navigating a dynamic operational environment. This entails fostering active learning pathways and trajectories while striving for increased levels of adaptive knowledge transfer (Ivaldi et al., 2022). The present study analysis reveals that organisational learning is critical for the effectiveness of Industry 4.0 and 5.0 technologies in a firm. There is a research gap in organisational learning on enhancing Industry 4.0 and 5.0 technologies use in manufacturing.

Research Gap 2: Organisational learning on relationship with effective implementation of Industry 4.0 and 5.0 technologies

Based on the fourth proposition of the study linked to objective 2, it can be proposed as follows:

Proposition 4: Organisational learning has a positive relationship with capabilities of the of Industry 4.0 and 5.0 technologies

3.6 Operations determinants and sustainable performance

Operational uncertainty significantly impacts process efficiency, sustainability practices, and firm profitability. This uncertainty can stem from external environmental, industry and business firm factors, as discussed earlier. Operational uncertainty can lead to inefficiencies in process design and execution. While operational uncertainty poses challenges, it also presents opportunities for firms to innovate and adapt. By investing in flexible and robust systems, such as dispatchable generators in renewable energy or advanced risk management practices in supply chains, firms can mitigate the adverse effects of uncertainty and potentially enhance their sustainability and profitability.

Sustainability refers to the capacity to attain environmental, social, and economic objectives in the present while ensuring the ability to uphold these objectives in the future without making any concessions. Sustainability is a reality from an ontological perspective and regulatory point of view (Ebrahimi & Koh, 2021). As indicated in Figure 3.8, in the present study, the proxies for sustained performance (SPF) were process efficiency, outcomes-driven sustainable practices and firm profitability. Process efficiency in manufacturing is a critical factor that influences competitiveness, cost-effectiveness, and customer satisfaction (Al-Rifai, 2024). Industry 4.0 offers new possibilities for the manufacturing industries to increase efficiency, decrease costs, and boost production based on these capabilities (Villani et al., 2018). Also, operational uncertainty impacts the optimal performance of operations, influences decision-making (Schuh et al., 2015; Vidal et al., 2023) disrupts the efficiency of the system at the design, operation, maintenance, and management levels (ElMaraghy et al., 2014; Alkan et al., 2018).

The pressure to centralise sustainability is evident at the global, country and business firm level (Koh et al., 2019). Increasing significance is attributed to adopting

environmental, social, and governance (ESG) practices (Schuh et al., 2015; Alsayegh et al., 2020). Social and environmental responsibility is crucial; although it might show short-term negative impacts in some cases, it has long-term benefits. Process efficiency in manufacturing is a critical factor that influences competitiveness, cost-effectiveness, and customer satisfaction (Al-Rifai, 2024). Industry 4.0 offers new possibilities for the manufacturing industries to increase efficiency, decrease costs, and boost production based on these capabilities (Villani et al., 2018). Also, operational uncertainty impacts the optimal performance of operations, influences decision-making (Schuh et al., 2015; Vidal et al., 2023) disrupts the efficiency of the system at the design, operation, maintenance, and management levels (ElMaraghy et al., 2014; Alkan et al., 2018). The pressure to centralise sustainability is evident at the global, country and business firm level (Koh et al., 2019). Increasing significance is attributed to adopting environmental, social, and governance (ESG) practices (Schuh et al., 2015; Alsayegh et al., 2020). Social and environmental responsibility is crucial; although it might show short-term negative impacts in some cases, it has long-term benefits.

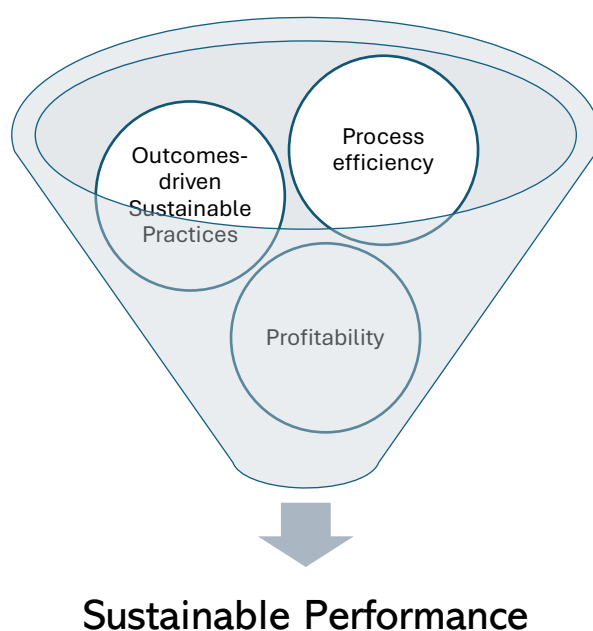


Figure 3.8: Proxies for sustainable performance

Source: Author

Firms need to incorporate the assessment of social and environmental consequences of their business activities alongside their economic performance. This is critical for the holistic view to guide decision-making and performance assessment within a firm. (Tang

et al., 2018) highlighted that little research has been conducted on sustainable production frameworks. As such, the social and environmental challenges have prompted a call for researchers and the manufacturing community to satisfy United Nations sustainability development goals (SDGs). The integration of environmental sustainability into the formulation of the SDGs is driven by the recognition that economic progress is contingent upon maintaining harmony with the environment. Thus, operations management decisions made by business firms are significant contributors to anthropogenic impacts on the ecosystem. Hence, it can be argued that implementing sustainable operations management practices holds significant potential in addressing humanity's various challenges (Swalehe et al., 2020). This requires developing tools that consider sustainability in decision-making (Tiwari & Khan, 2020).

High-performing firms embrace priorities that best meet the conditions of the environment, particularly stability and dynamism (Badri et al., 2000; de Waal, 2021; de Waal & Kraaijveld, 2022). These firms adopt competitive priorities, which accept their environment and set up the mechanism to react to the forces it exerts. Mitigating operational uncertainty (OPU) can indeed lead to improved sustainability outcomes and increased firm profitability. Thus, mitigating uncertainties directly impacts profitability by improving decision-making and operational efficiency. (Fu & Madni, 2024) explained that firms that learn from successful frameworks and adapt to changes can maintain productivity and profitability even in uncertain conditions. Based on the review, proposition 5, which is linked to objective 3, can be highlighted as follows:

Proposition 5: The combinations of OPU, IRT, and OLN conditions lead to high or low sustained performance (SPF).

3.7 Chapter conclusion

As this study focused on understanding and managing operational uncertainty, this chapter discussed configurations - causal conditions and outcomes. It reviewed configurations (combination of factors) leading to sustainable performance in manufacturing. This is linked to empirical research on operational uncertainty, which in manufacturing can lead to significant complexity within processes, decision-making, and overall management. Nine operational uncertainty constructs were identified at the external environment, industry, and firm levels. As such, there is a need for causal conditions to manage, which in this study are the Industry 4.0 and 5.0 technologies

complemented by organisational learning. The emergence of Industry 4.0 and 5.0 technologies is fundamentally changing the responses by firms and their approach to increased challenges of operational uncertainty.

Chapter 4

Operationalising Configurational Theory

4.1 Introduction

This chapter elevates the study's theoretical and methodological positioning and links the theory in Chapter 2 and the empirical review of configurations in Chapter 3 with the methodological introductions. Linking theory to methodology in research is critical to conducting robust and meaningful studies as this ensures that research is grounded in a solid theoretical framework and employs appropriate methods to address research questions effectively (Chan & Clarke, 2019; Mejía Trejo, 2023). This connection enhances the validity and reliability of research findings, providing a comprehensive understanding of the phenomena under investigation.

Linking theory and methodology operationalise the configurational theory with qualitative comparative analysis (QCA) (Park & Mithas, 2020). This is followed by analysing the capabilities of the QCA in theory building and development. This chapter then synthesises the different types of QCA followed by QCA as a research method and its integration with other methods. This is followed by the closing of the methodological research gap, highlighting the contribution of the research study. The last part of this chapter provides the configurational model of the study. This is a critical transition before presenting Chapter 5 – design and methodology.

4.2 Operationalising Configurational Theory with QCA

Qualitative comparative analysis (QCA) employs set theory logic to characterise causal complexities (Cheng et al., 2022; Fiss, 2011; Misangyi et al., 2017). By applying set-theoretic methods, research can uncover non-standard configurations, thereby enriching the discourse on how organisations can effectively navigate complexity and achieve success in diverse manufacturing contexts. Thiem (2016) explained that the QCA represents a highly formalised configurational comparative method that utilises Boolean algebra instead of linear algebra, emphasising the logic of implication over covariation and focusing on conjunctural causation rather than simple interaction effects. This approach allows research to identify patterns and causal recipes that explain complex phenomena (Fiss et al., 2013). The QCA operationalises this by identifying multiple configurations of causal conditions leading to the same outcome, demonstrating

equifinality. The literature review highlights some of the leading theories consistently used in QCA. These include fuzzy set theory, complexity theory, INUS theory of causality, configurational theory, planned behaviour theory, chaos theory, and motivation theory (Geremew et al., 2023; Krupnik et al., 2023; Mejía Trejo, 2023; Plugge & Nikou, 2024; Woodside et al., 2018). Several authors have used QCA set-theory methods to identify and analyse configurations based on configurational theory (Byrne, 2005; Huang et al., 2024; Van Nguyen et al., 2024; Park & Mithas, 2020). Traditional models often assume rational behaviour but, importantly, incorporating behavioural and cognitive factors can enhance the relevance and applicability of operations management theories (Gino & Pisano, 2008). This is possible as other disciplines have successfully integrated behavioural insights, suggesting that operations management could benefit from similar adaptations to better reflect real-world complexities

Parente et al. (2019, p. 401) posited that "QCA is only applicable for studies that seek to offer theoretical contributions from a configurational perspective. It will also be useful only if the intention is to unravel causal complexity relations ". This supports the choice of QCA as an appropriate method for the present study.

4.3 QCA as a research method and types of QCA

4.3.1 QCA as a research method

Ragin (2009) argued that this is an ideal method for assessment of the 'combined effect' as well as the 'interaction relationship'. Thiem (2016) posited that Qualitative Comparative Analysis (QCA) is one of the most formalised configurational comparative methods as it integrates both qualitative and quantitative methods. It is a method that was introduced in the 1980s as a comparative analysis to evaluate causation (Ragin, 2008a). This involves examining relationships by systematically identifying the membership of configurations (Leppänen et al., 2019). The approach integrates both case-oriented and variable-oriented approaches to effectively model multiple realities with complex antecedent configurations (Thai & Wang, 2020). Pappas and Woodside (2021) explained that the QCA uses combinations of causal conditions that result in an outcome. Huang et al. (2024) argued that the QCA allows causal complexity analysis and multiple interaction effects associated with conjunctural, causation equifinality and causal asymmetry that are difficult to capture using conventional research methods.

4.3.2 Types of QCA

The literature indicates that there are six general types of QCA: crisp-set QCA (csQCA), fuzzy-set QCA (fsQCA), comparative fuzzy-set-QCA (cfQCA), multi-value QCA (mvQCA), geographic QCA (geoQCA), and temporal QCA (tQCA) (Denk & Lehtinen, 2014; Greckhamer et al., 2018; Huang et al., 2024; Schneider & Wagemann, 2012; Van Nguyen et al., 2024). Table 4.1 presents an overview of these types of QCA.

Table 4.1: Type of QCA methods

Type	Description	Reference
Crisp-set QCA (csQCA)	It is based on binary conditions and outcomes with binary values (0 or 1) using categorised data	Marx and Dusa (2011)
Fuzzy-set QCA (fsQCA)	It is based on a degree of membership of the causal conditions, which range from 0 to 1.	Cheng et al. (2022); Huang et al. (2024) ; Pappas (2018); Marx and Dusa (2011)
Comparative fuzzy-set-QCA (cfQCA)	It is based on characteristics of fsQCA but compares multiple sets of conditions in different research contexts	(Mejía Trejo, 2023)
Multi-value QCA (mvQCA)	It is based on dichotomous outcomes but with causal conditions with three or more categories	(Rushdi, 2018) (Vink & Van Vliet, 2009)
Geographic QCA (geoQCA)	It is based on QCA, which incorporates geographic information systems	(Gao & Lei, 2023)
Temporal QCA (tQCA)	It is based on QCA in a temporal context, analysing how conditions and outcomes evolve over time.	(Niessen, 2024)

Source: Author

The most well-researched and developed of these methods are csQCA and fsQCA (Van Nguyen et al., 2024). Marx and Dusa (2011) explained that the csQCA identifies configurations of conditions affecting outcomes based on dichotomised values into true (1) or false (0) for full or non-membership, respectively. This is different from the fsQCA, which employs fuzzy-set logic, allowing for the analysis of complex causal relationships with varying degrees of membership (Huang et al., 2024; Pappas, 2018).

4.4 Capabilities of QCA in theory extension and testing

As indicated, QCA is a valuable method for both theory building and testing (Oana et al., 2021; Misangyi et al., 2017), supporting the earlier assertions of Greckhamer et al. (2013)

who, argued that configuration analytical models are useful in theory building, theory extension and theory testing. Thus, QCA is used for theory building by identifying necessary and sufficient conditions for outcomes, particularly in complex causal relationships. It is increasingly used across various disciplines to synthesise evidence and develop theories. Pappas and Woodside (2021) also employed a configurational approach to analyse a theory, while Cooper and Glaesser (2016) demonstrated the value of using asymmetric tests to both advance theory and provide useful empirical models of the occurrence of multiple realities. The QCA allows research to systematically compare cases and identify necessary and sufficient conditions for outcomes. It facilitates the exploration of complex causal relationships and helps formulate theoretical propositions. Through its configurational approach, QCA enables testing these propositions against empirical data, thereby contributing to the refinement of theories and enhancing the robustness of research findings. The QCA can be applied using the deductive approach for theory testing and the inductive approach for theory building.

Iannacci and Kraus (2022) explained that in contrast to a strictly deductive method that depends on theoretical reasoning instead of empirical data, QCA could be employed to bridge the gap between theoretical knowledge and empirical evidence. Additionally, QCA can also be employed to develop middle-range theory, often in the form of substantive theory, to advance knowledge in a specific area of inquiry instead of a purely inductive approach. Huang et al. (2024) followed the inductive mode of reasoning or approach in theory-building employing multi-methods: grounded theory method combined with fsQCA. Kreiser et al. (2021) followed deductive reasoning for theory-extension using a mono-method: quantitative survey. This shows the versatility and relevance of the QCA for theory-building, extension, and testing.

4.5 Integrating QCA with other methods

Oana et al. (2021) suggested that the robustness of (QCA) results is a high priority for methodologists and practitioners. Research employing QCA can assist in identifying and analysing various configurations of conditions that lead to specific outcomes, allowing for a nuanced understanding of how different factors interact. This is guided by the three pillars of conjunctural causation, equifinality, and asymmetric causality (Meuer & Fiss, 2020). There is a growing number of studies where fsQCA is integrated with other methods, especially PLS-SEM. Rasoolimanesh et al. (2021) developed guidelines for the

combined use of PLS-SEM with QCA to analyse complex relationships. This approach effectively leverages symmetric and asymmetric approaches, offering a comprehensive framework for understanding multifaceted organisational phenomena. (Acquah et al., 2023). Acquah et al. (2023) employed both symmetric (PLS-SEM) and asymmetric (fsQCA) data analysis methods to explore how different total quality management practices influence operational performance and identify various combinations of these practices that lead to improved outcomes. Sukhov et al. (2023) employed an integrated approach using PLS-SEM, necessary condition analysis (NCA), and fsQCA for informed decision-making. Other research also compared the results by employing PLS-SEM and QCA as contrasting statistical techniques to explore and compare the results (Duarte & Pinho, 2019)

The integration of PLS-SEM and QCA enhances the understanding of causal relationships by combining the strengths of both methods. This combination is advanced in the present study, which can be used to validate relationships and identify new ones (Richter et al., 2022) and can be complemented with QCA by analysing how different configurations of variables lead to specific outcomes, offering insights into the sufficiency of conditions for an outcome (Rasoolimanesh et al., 2021). It also assists with complementary causal perspectives, and this dual perspective helps in understanding the causal complexity and interdependencies among variables, which is crucial for developing comprehensive causal models. Despite this enhanced predictive and explanatory power and complementary causal perspectives, there is a methodological gap associated with such analysis and a need for further research.

Methodological gap 2: The integrated QCA studies need attention to incorporate a method for optimising causal conditions

Based on the methodological gap 2 and linked to objective 3, the sixth proposition can be highlighted as follows:

Proposition 6: Integration of optimising methods is necessary for optimum outcomes of QCA-based methods

This can be done by increasing the number of studies with an integrated approach in operations management, which currently are very few, as well as incorporating an approach for optimising the causal conditions. This is necessary as the strength of the

QCA lies in the small number of causal conditions. The inclusion of optimising methods can further advance this debate with methods such as fuzzy decision-making trial and evaluation laboratory (DEMATEL) as it can identify the causal and effect causal conditions (López-Ospina et al., 2022; Yeh & Huang, 2014). The non-deterministic multi-criteria decision-making (MCDM) tool involves a degree of uncertainty or ambiguity. Non-deterministic MCDM methods incorporate fuzzy sets, possibility, and belief function theories to manage imperfect information (Tacnet et al., 2017). Hence the use of fuzzy-DEMATEL. This study can contribute to the ongoing debate within QCA regarding which of its main solution types should be prioritised for substantive interpretation, arguing for an integrated approach to understanding these solutions (Haesebrouck, 2022).

Thus, by analysing the complementary strengths of the three QCA solution types, emphasising that the parsimonious solution identifies causally relevant conditions, the conservative solution identifies contextually irrelevant conditions, and the intermediate solution addresses ambiguous conditions that may not be clearly relevant or irrelevant. Core texts have supported the selection of the intermediate solution (Ragin, 2008a). Recent critiques from some scholars have emerged, favouring a more parsimonious solution than an intermediate solution (Thiem, 2022). This debate is ongoing and highlights various inconclusive elements of the present state. The evaluation of solution types is notably defined by varying criteria, implicitness regarding these criteria, and the necessary background assumptions for making causal inferences, as well as differing analytical objectives within the framework of configurational theorising (Haesebrouck, 2022).

4.6 Theory-extensions, configurational model and propositions

4.6.1 Theory extension

The present research focuses on theory extension, introducing extension in theoretical and methodological perspectives. Using QCA in configurational theory systematically explores how different conditions interact to produce specific outcomes, offering a nuanced understanding of causality (Huang et al., 2024). Plugge and Nikou (2024) also support this view, arguing that configurational theory is integral to QCA as it facilitates the examination of complex causal relationships within systems. Misangyi et al. (2017) argued that QCA emerged as part of the second wave of configurational management development. This is to deal with the "void in tools capable of fully capturing causal

complexity [as] conventional correlation-based approaches are not designed to address conjunctural, equifinal, and asymmetrical causal relations" (Misangyi et al., 2017, p. 256). Miller (2018) acknowledged the work of Misangyi et al. (2017) but deemed the new approach deviating from the older approaches to configuration theorising and strengthening to ensure it is robust. This author recommended "approach related to strengthening empirical research using QCA and the various clustering approaches.". These included "use of theory and conceptual debates to guide the research", "blend quantitative and qualitative analyses", "employ case narratives to guide research scope and interpret profiles" and "Establish the significance of configurations"

Theory building focuses on the process through which a new thought or metaphor leads to constructing a conceptual model that helps to better describe the topic. Developing theories is essential for increasing management understanding, albeit a challenging task (Shepherd & Suddaby, 2017; Mollah, 2019). A theory is "good" if it satisfies the qualities (criteria) for "good" theory, which include the following: originality, parsimony, internal consistency and generalisability (Gay & Weaver, 2011). Theories are developed to explain, predict, and comprehend phenomena, and they frequently push the boundaries of current understanding while expanding it (Shepherd & Suddaby, 2017; Paul et al., 2024). Multiple theories offer the opportunity to view the same issue through different lenses. Therefore, it is up to particular research to determine which perspective it employs or adheres to, to construct an argument, define the background of the problem, and explain findings. The critical components of a theory are variables, constructs, and their relationships. A variable is also known as an observed unit empirically operationalised by the measurement. In contextualising this, Andrade (2021) posited that variables need to be operationalised, meaning they need to be defined in a manner that makes it possible to precisely measure those variables. Variables are utilised to depict the characteristics of the sample being analysed and are referred to as such due to their tendency to fluctuate in value across the subjects within the sample (Calder et al., 2021; Kaliyadan & Kulkarni, 2019).

The theory is viewed as a system comprising constructs and variables related to propositions and hypotheses. Bacharach (1989) explained constructs as approximated units as they cannot be directly observed, while variables are observed units and are empirically operationalised by measurement. Guided by the boundaries, the theory evaluation can be done with propositions or hypotheses. At an abstract level,

propositions are used to evaluate the relationship among the constructs, while at a detailed level, hypotheses are preferred for analysing the relationship among the variables (Bacharach, 1989). Study propositions are essential for ensuring internal validity in research. They provide valuable insights into the precision of definitions, measurements, associations, and confounding factors that are taken into account during the course of the study (Ulaga et al., 2021). Propositions serve as the foundation for deducing inferences in the context of external validity (Cornelissen, 2017; Ulaga et al., 2021). They can also be developed for future research, assisting in reducing potential relevance gaps within a study of a particular phenomenon.

The hypothesis posits a proposed association between two or more variables. A noteworthy association between an independent variable and a dependent variable does not establish causality. This association may be partially or entirely accounted for by one or more confounding variables. The other component of the theory is the construct, which is an approximated unit that cannot be observed directly in research. A construct is an abstract idea that is explicitly chosen (or "created") to explain a particular phenomenon (Kivunja, 2018). A construct can be either a unidimensional or a multi-dimensional construct, and it can be either a basic notion or a composite of a collection of numerous connected underlying concepts. Scientific research conceptions need specific definitions that others may use to grasp precisely what they mean and do not mean. Bacharach (1989) argued that the variables and constructs are related by hypotheses and propositions, respectively. If an obtained relationship finds a correlation between two empirical variables, it could point to either (a) the same theoretical construct being reflected by both variables or (b) two related but distinct theoretical constructs. Evidence supporting a different conclusion resulting in rejection of the hypothesis is proposed when relationships are shown to be dynamic, nonmonotonic, and/or asymmetric (Tesser & Krauss, 1976).

4.6.2 Emergent core tenet, boundaries, and conceptual model

The identification of the core tenets of the emergent theory (Hindriks, 2022), its boundaries (Bacharach, 1989), and the conceptual framework (Grant & Osanloo, 2014; Luse et al., 2012) is important in the theory extension.

4.6.2.1 Emergent core tenets

Over and above unifying the theories, extracting the core tenets of the emergent theory or approach is critical, mainly when theories are not in their original form (Guala & Hindriks, 2015; Hindriks, 2022). Jaccard and Jacoby (2010) argued that the fundamental components of a theory include its assumptions, tenets, assertions, propositions and predictions. These elements collectively form a shared framework that researchers in a given field can utilise to explore the significance and validity of real-life experiences and provide a solid foundation for conducting research within that field.

4.6.2.2 Identify boundaries of the theory

In addition to the core tenets, it is critical also to highlight the boundaries of the theory, as they highlight the assumptions of the theory and help set the limitations in applying the theory. These assumptions entail implicit values and explicit restrictions on space and time. Bacharach (1989) posited that the generalisation of the theory increases from being bounded by space and/or time to being unbound by both space and time. This is indicated in Figure 4.1.

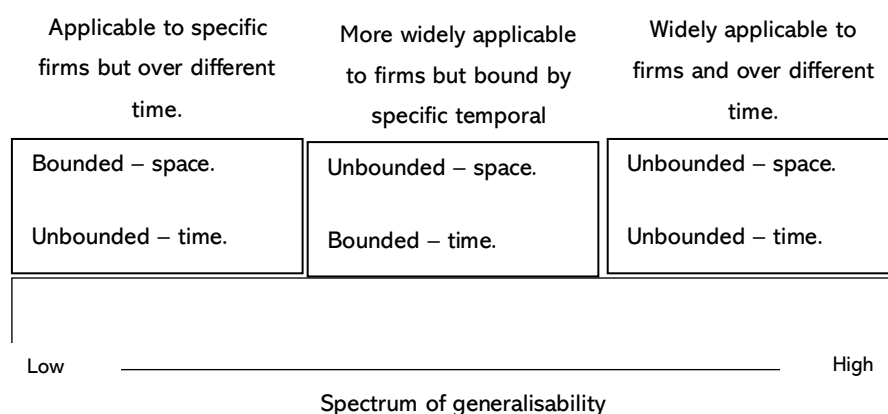


Figure 4.1: The spectrum of generalisability in theory development

Source: Developed from the literature of Bacharach (1989).

4.6.2.3 Conceptual framework

A conceptual framework functions as a road map for the study, enabling the researcher to visualise and implement the research project as it helps to delineate the scope of a study and establish its theoretical foundations. It provides guidance and momentum to the research inquiry, helps stimulate research, and ensures the extension of knowledge.

Most conceptual frameworks take the form of diagrams in which the links between the constructs and variables involved in the study are graphically represented using arrows. The core tenets of the theory can be used to develop the conceptual model and identify the variables pertinent to the study and their potential relationships. Conceptual frameworks serve distinct purposes in various categories of research. They may be used to generate hypotheses for explanations and predictions or to determine survey questions or data points. A conceptual framework is a set of interconnected ideas that helps provide a picture of the relationships between concepts in a study and their theoretical underpinnings. It is more than a list of ideas; it is a chance to highlight an epistemological and ontological perspective and the research approach (Grant & Osanloo, 2014). The conceptual framework can also describe and refine the problem's underlying notions (Luse et al., 2012).

Greckhamer et al. (2018) argued that QCA requires a more robust establishment relative to correlation research; hence, it is essential to formulate configurational reasons to substantiate the causal circumstances employed to elucidate the outcome. The present research developed a configuration model to explain sustained performance. Figure 4.2 depicts a set-theoretic configuration model that conceptualises the constructs and demonstrates their multiple asymmetric relationships. Sustained performance may manifest or not through various combinations of constructs, including operational uncertainty, Industry 4.0 and 5.0, and organisational learning. The outcomes of interest are analysed using Boolean minimisation.



Figure 4.2: Configurations of the study

Source: Author

4.6.3 Theory evaluation

Bacharach (1989) argued that falsifiability and utility should be used as the two criteria for evaluating the theory. Falsifiability evaluates whether the theory is constructed so that it is empirically refutable. At the same time, utility analyses determine whether the theory is useful, can be explained, and can predict the constructs, variables, and their linkages. Utility evaluates whether the theory includes both the logical, which involves scope, and the empirical, which provides for explanation and prediction.

4.6.3.1 Falsifiability to evaluate the theory

Good theory-building research methods are those that, like a theory itself, specify their variables, narrow their focus to a specific topic, construct coherent causal chains, and offer concrete hypotheses (Wacker, 1998). Such research should follow comparable procedures, regardless of study methodology, to become integrative. The operationalised variables must be coherent and part of a good measurement model for the falsification of variables. This entails face and construct validity. Face validity is usually an informal review of the survey instrument by non-experts for clarity and appropriateness with the target sample, while experts familiar with both the topic being studied and the measuring tools are used to conduct content validity. In addition, variables must have adequate variance for logical analysis and adequate reliability, which is important for stability. The *falsifiability of the constructs* should be determined with exploratory factor analysis, convergence validity, discriminant validity, and predictive validity, amongst others.

4.6.3.2 Utility to evaluate the theory

Utility focuses on the scope as well as explanatory potential and predictive adequacy during theory building. The scope must ensure that the variables included in the theoretical system are sufficient but parsimonious (Bacharach, 1989). A confirmatory tetrad analysis can assist as it determines statistically whether a variable of the construct is best specified as reflective and a formative construct (Gudergan et al., 2008; Mtotywa & Kekana, 2023). It is essential to confirm this to ensure that the measurement model is accurate and acceptable. In reflective constructs in a model, not all variables need to be present to be acceptable. However, for formative constructs, all variables should be retained. In the analysis, if tetrads are not significantly different from zero, $\tau = 0$, the

model is reflective. Predictive relevance helps with the evaluation of the model. A $Q^2 > 0$ indicates a good predictive relevance (Hair et al., 2019).

4.7 Chapter conclusion

This chapter presented the operationalising theory, which is a configurational theory with QCA that links the theory and methods. This is important as neglecting the linkage between theory and methodology in operations management research can lead to significant theoretical and practical challenges. This chapter details QCA as a method, highlighting the different types, with csQCA and fsQCA being the most common ones, and how the QCA can be integrated with other methods in research. It also provides insights into the capabilities of QCA to build theory, theory-extension and test theory, with the last part of the chapter providing the approach to theory adoption and the configurational model of the study. The next chapter (Chapter 5) provides the methodology followed to evaluate the extended theory.

Chapter 5

Research Design: Methodology and Methods

5.1 Introduction

Chapter 4 described operationalising the configurational theory with QCA and the configurational model and generating research propositions. Chapter 5 presents the study's design, following the paradigm and methodology. Research must be clear regarding research design, paradigms, methodology, and approaches to effectively address the research problem. This understanding is crucial for making decisions about data collection, analysis, interpretation, and reporting findings (Dawadi et al., 2021; Mkansi & Acheampong, 2012). The methodology examines the numerous processes used to conduct the research and their rationale (Langer, 2018; Patel & Patel, 2019; Sileyew, 2019). Langer (2018) explained methodology as the “how” part of the research, a crucial part that complements the “what” to investigate and “why” the investigation is needed. This is followed by the research approach, which can be the deductive, inductive, or combined approach (Bell et al., 2022). Plano Clark and Creswell (2009) posited that deductive research works from the 'top-down,' from a theory through hypotheses to facts to support or refute the theory. On the other hand, inductive research works from the 'bottom-up', using the participants' perspectives to develop bigger themes and generate or adapt theory that interconnects the dimensions.

The following section describes the population, sample, and sampling, which focuses on the target population, unit of analysis, sample size, sampling method and techniques, and sample frame. The final section describes the methods, which include the data gathering process, highlighting the research instruments and empirical data collection approach, data analysis approach, and quality control - validity and reliability of the study. The last part of this chapter describes the study's ethical considerations (Leedy & Ormrod, 2023) and methodological limitations, highlighting the research's technical and administrative challenges.

5.2 Research design

After defining the research problem, research design is the most vital and logical plan (Mukherjee, 2017). The present study employed a multi-quantitative method design from a singular paradigm (Morse, 2003; Hunter & Brewer, 2015; Wellman et al., 2023).

5.2.1 Rationale for the use of a multi-quantitative method

The multi-method is beneficial in research as it has the ability to generate and test theory in a single study (Wellman et al., 2023). Hunter & Brewer (2015), emphasised that multi-method research employs a research plan that incorporates multiple data collection methods and/or multiple data analysis methods. The multi-quantitative design uses various quantitative techniques in a single research study to address different aspects of research (Marquart, 2017). Central to an effective rationale is explaining why and how the methods are being combined, ensuring theoretical and operational alignment, and ensuring that measures are interconnected in the different stages of the research (Wellman et al., 2023). The research employed different quantitative methods in parallel to strengthen its robustness. In addition, considering the different dimensions of the research can provide a comprehensive and more complete picture. It also helped to increase the present study's validity and flexibility in the approach adapted to deal with the complexity of the research problem.

One phase used expert assessment, while the other used a survey. Brownstein et al. (2019) argued that valid statistical and scientific analyses require the use of expert judgment. Despite this, these authors cautioned regarding clarity surrounding the usefulness of judgment in terms of how, when, how frequently, and from whom it is beneficial, as opposed to producing biased and nonreproducible outcomes. Expert judgment is indispensable and inclusive at all stages of scientific research. The scientific conclusion is achieved by combining expert judgments from content specialists and statisticians, focusing on carefulness, rigour, transparency, and objectivity. This approach emphasised the importance of expert judgment and the statistical quantification of uncertainty. This is because decisions should strive for maximum objectivity and be grounded in data that will be provided as soon as they become available. The survey was necessary to obtain information from the manufacturers across the different manufacturing industries and across South African provinces to improve the chances of

generalisability of the study. This is critical as survey research historically includes large population-based data collection.

Choi et al. (2016) posited that adopting multi-methods significantly advances the field of operational management. This makes the research more scientifically sound, rigorous, and practically relevant. By combining multiple methods, researchers can explore problems in multiple dimensions, leading to novel and scientifically sound managerial insights. Huang et al., (2024) also used the multi-method research design for assessing complex problems based on the configurational theory approach. Regarding theoretical and operational alignment, as discussed in previous chapters, the research is grounded in complexity theory and operationalised with configurational theory. Alavi et al., 2018) supported by Chan and Clarke (2019) promoted such an alignment, urging researchers to develop a theory that is linked to the research methods that ensure that they are effective in drawing robust research conclusions. Additionally, operational alignment in multi-method research focuses on ensuring that the measures are interconnected in the different stages of the research. This was ensured by having various ways of effectively measuring variables to capture the same underlying theoretical concepts of interest (Wellman et al., 2023) – conditions and outcomes.

Within this study's multi-method design, the fuzzy-QCA is the main method, also known as the set-theoretic method, which is grounded on the study's operationalising theory - configurational theory, a useful theory for causal complexity (Fiss, 2007; Ragin, 2008a). The configurations approach reveals coherent patterns of business firms by identifying interpretive schemes and the "how" they connect to characteristics and structural processes (Harlacher & Reihlen, 2014; Damke et al., 2018). Although cases can be interpreted in various ways, such as theoretical entities or empirical units, QCA specifically conceptualises cases as sets of attribute configurations (Misangyi et al., 2017; Greckhamer et al., 2013).

5.2.2 Design of research

Huang et al. (2024) argued that the QCA allows causal complexity analysis and multiple interaction effects associated with conjunctural, causation equifinality and causal asymmetry that are difficult to capture using conventional research methods. The fuzzy QCA requires developed constructs (Rihoux & Ragin, 2009). As indicated in Figure 5.1, such multiple data collection approaches and other data collection and analysis methods

were performed to ensure streamlined and valid constructs. In the present study, expert judgment assessment (Brownstein et al., 2019) and a questionnaire survey were the two data collection methods, while the data analysis methods included the PLS-SEM and fuzzy-DEMATEL and fcQCA

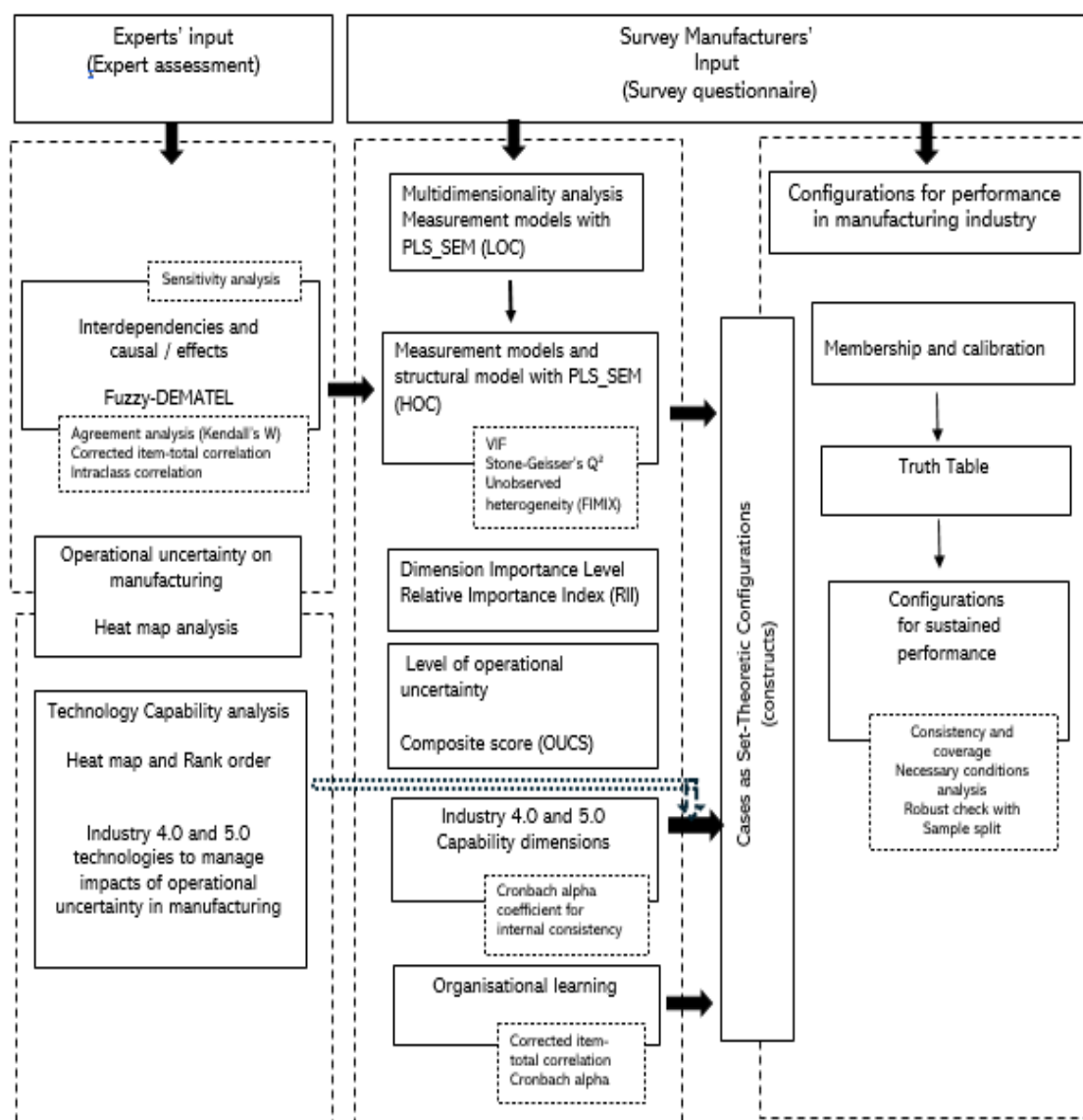


Figure 5.1: Design of the research

Source: Author

5.2.3 Summation of steps to avoid pitfalls in using multi-method design

The study rationale and design ensured that pitfalls were avoided when using the multi-method. Wellman et al. (2023) highlighted the main pitfalls when employing multi-

method design as follows: Firstly, there is poor justification for using multi-methods. This was explained based on the why and how, theoretical and operational alignment, and interconnectedness of the measures. Secondly, there are challenges with “Methodological Fit” – alignment of theory and methodology (Edmondson & Mcmanus, 2007). In this research, there is a fit between the contextualising or grounding theory and operationalising theory, as well as the operationalising theory and designs, including the methods and measures. Lastly, poor theoretical complementarity between studies. In the present study, there is clear complementarity between experts and surveys.

The experts not only help to distinguish between the causes and effects of operational uncertainty, but they also identify the impact of the operational uncertainty dimensions on manufacturing and identify the Industrial 4.0 and 5.0 technologies that can effectively manage the impact of operational uncertainty. This complements the manufacturing firms' survey, highlighting their current state. In developing the configurations for sustained performance, the research focused on configurations from causal conditions and effectively selected the technologies for managing these causal conditions.

5.2.4 Linking objectives, propositions and methods

Research effectively links its objectives to relevant propositions and research methods by ensuring coherence between the study's aims and the chosen methodologies. This involves a systematic approach in which the objectives inform the research design, guiding the selection of appropriate data collection and analysis techniques. The alignment of these elements is crucial for producing reliable and meaningful research outcomes. There is a need to align objectives and propositions to ensure coherence in the research design. This alignment facilitates a structured approach to investigating the research problem. As indicated in Table 5.1, the research links the objectives, propositions, and source of data and analytical methods.

Objective 1 is linked to propositions 1 and 2, focusing on understanding operational uncertainty using business firm surveys and expert assessments. This objective was investigated with the scatter plot, corrected item-total correlation, and the measurement model of the structural equation modelling partial least squares (PLS-SEM), fuzzy-DEMATEL, higher-order construct measurement model, and structural model for operational uncertainty and sustained performance. Objective 2 is linked to propositions 3 and 4 and is analysed with expert assessment based on mean and standard deviation

and a heatmap-based method and firm survey using Pearson correlation analysis. Objective 3 is linked to propositions 5 and 6. It utilised the survey data from the business firm to conduct a Fuzzy-set qualitative comparative analysis (fsQCA).

Wisenthige (2023) argued that good research design includes neutrality, reliability, validity, and the ability for generalisation, aiming to provide accurate and unbiased research insights. Furthermore, it ensures that there were no mismatched objectives and propositions in the research. This can significantly undermine the validity and reliability of findings, leading to questionable conclusions and potentially flawed applications. This can create measurement bias, where the instruments and methods do not accurately capture the latent constructs of interest, thus leading to invalid results. The mismatch can also result in selection bias, where inappropriate sample selection may result, thus affecting the generalisability of the findings (Villasís-Keever et al., 2018).

Table 5.1: Objective, proposition, and methods of research

Objective	Propositions	Data collection methods (Empirical data)	Analytical method
Objective 1: Develop a comprehensive understanding of operational uncertainty in manufacturing.	Proposition 1: Operational uncertainty is a multi-dimensional construct	Firm survey Expert assessment Firm survey	Measurement model Lower-order constructs (dimensions) Fuzzy-DEMATEL Measurement and Structural model Higher-order construct (operational uncertainty)
	Proposition 2: Operational uncertainty is a norm in the manufacturing sector, as not all relevant information is already known to decision-makers	Firm survey	Relative Importance Index (RII) Composite Score
Objective 2: To review and validate the capabilities of fourth and fifth industrial revolution technologies in manufacturing operations and linkage to organisational learning.	Proposition 3: Industry 4.0 and 5.0 technologies capabilities can manage the operational uncertainty in the manufacturing sector	Expert Assessment	Heatmap analysis
	Proposition 4: Organisational learning has a positive relationship with the capabilities of Industry 4.0 and 5.0 technologies.	Firm survey	Correlation matrix analysis
Objective 3: Formulate and analyse sustainable performance configurations (outcomes condition) with causal conditions - operational uncertainty, Industry 4.0 and 5.0 technologies and organisational learning.	Proposition 5: The combinations of OPU, IRT, and OLN conditions lead to high or low sustained performance. Proposition 6: Integration of optimising methods is necessary for optimum outcomes of QCA-based methods	Firm survey	Fuzzy-set qualitative comparative analysis (fsQCA)

Source: Author

5.3 Research paradigm

The research paradigm concerns how knowledge is created (Crotty, 1998; Madden, 2022; Scotland, 2012) Saunders (2009) termed this the research philosophy, while (Creswell & Creswell, 2017) named it the philosophical worldview.

There are multiple research paradigms, with the most common in business and social studies being positivist or post-positivist, constructivist or interpretivist, transformative, and pragmatism (Creswell & Creswell, 2017; Saunders, 2009). Research uses the research paradigm, which contains crucial assumptions about the beliefs, reality, knowledge, and value in research. This study employed the post-positivist paradigm (Wang et al., 2007), based on the belief that an objective reality can be studied and measured (Howell, 2012; Kankam, 2019). However, the unique perspective on the relationship between knowledge and the method by which it is generated is likely to have the most influence (Saunders, 2009). The post-positivist paradigm emerged in response to the constraints of the positivist paradigm (Scotland, 2012).

Positivism prioritises objectivity, quantification, and the search for universal rules through empirical observation and logical reasoning. In contrast, post-positivism acknowledges reality's contextual nature, which can have inherent complexities (Lim, 2023). More importantly, the post-positivist paradigm recognises that all observations are fallible and theory-laden. This advances the view that scientific development is not merely a linear accumulation of factual information. Instead, it entails an ongoing interaction between theory and observation, in which theories provide guidance for observations, and observations might prompt the adaptation of the theory. Saunders, (2009) and Scotland (2012) explained that there are several ways of thinking about research paradigms, which comprise ontological position, epistemological position, axiology, and methodology. Ontology is concerned with the nature of reality. More than epistemological problems, this raises questions about the researcher's ideas about how the world operates and their adherence to particular viewpoints. The two parts of the ontology described in the present study each have their followers among business and management scholars. In addition, many scholars are likely to recognise them as creating valid knowledge posited that research that operates within a post-positivist framework possesses a critical realist ontology. Yeung, (1997, p.54) noted that “critical realism is as much against totalisation as relativism and to a critical realist, all knowledge is fallible but not equally fallible”.

Lim (2023) argued that critical realism, a concept linked to the post-positivist paradigm, recognises the presence of objective reality. However, it suggests that researchers' comprehension and interpretation of this reality may be influenced by factors such as mental processes and senses, making it prone to errors or biases. Critical realism questions the concept of a single, ascertainable "truth" and instead advocates for the presence of numerous, situation-specific "truths". This perspective promotes an analytical involvement with the research subject and the research process, stimulating interrogation, evaluation, and a reshaping of our comprehension of the world.

Epistemology is what constitutes acceptable knowledge in a certain field of study (Scotland, 2012). The central epistemological question is: "Can the approach to studying the social world, including management and business, be the same as the approach to researching the natural sciences?". The answer to this question provides insight into the acceptability of research-based knowledge. Axiology is a discipline of philosophy that examines value judgments (Suprpto, 2021). In axiology, an aspect of the philosophy of science, questions like "Why do we do science?" and "How can we put what we learn to use?" are explored. Axiology investigates the worth and benefits of science and aims to discover the nature and usefulness of scientific endeavours.

The advantages of philosophical understanding and approaches to problem-solving are outlined in axiology. Axiology is the study of truth claims and the values assigned to them as parameters (Suprpto, 2021). It also demonstrates a number of guidelines that must be taken into account when actually doing science (Srinivas, 2008). When numerous facets of human existence are considered, the axiological method encourages scientists to use their knowledge for greater benefit. Furthermore, the importance of the researcher's personal values of the researcher at every stage of the research process to the credibility of the findings cannot be overstated (Prat-i-Pubill, 2018). There is an importance of technological axiology research and advanced that it is of great theoretical and practical value. In terms of practice, it is the inner need for healthy development of technological practice, a strategic need for long-term need for sustainable development. Theoretically, it is helpful for the development of new theoretical investigations. Guba and Lincoln, (1994) advised that methodology focuses on how research investigation can proceed with the goal of learning what is required.

5.4 Research approach

This study used fuzzy-set qualitative comparative analysis (fsQCA), which uses Boolean algebra to conduct a case-based analysis to investigate interconnectedness, causation, and causal relationships (Ragin, 2008a; Misangyi et al., 2017). The fsQCA can be applied using the deductive approach for theory testing and the inductive approach for theory building (Huang et al., 2024; Kreiser et al., 2021; Pappas & Woodside, 2021). This study employed inductive logic, moving from evidence to theory.

5.5 Data collection methods

The data collection methods provided comprehensive insights into the research setting, which is the manufacturing industry. The data were collected, followed by an analysis of the population and unit of analysis, sampling methods and sample size, and instrument and data gathering methods.

5.5.1 Research setting – manufacturing industry

The physical, social, or experimental context in which research is carried out is referred to as the research setting. It is essential to provide an accurate description of this context because the findings and how they are interpreted may be significantly reliant on it. The manufacturing, construction, and engineering together constitute the secondary sector, which converts raw materials into finished products through the use of a more effective method (Alshehhi & Oláh, 2017). As explained in Chapter 1, the manufacturing sector is extremely important to the country's growth prospects in the years to come with respect to its contribution to economic development and employment.

There are ten industries in manufacturing, and these are by size, based on income - Coke, petroleum, chemical products (25.8%), food products and beverages (22.6%), transport equipment (17.1%), metals, metal products, machinery & equipment (16.3%) and others - wood, wood products, paper, publishing & printing (6.1%), furniture & other manufacturing (3.5%), glass & other non-metallic mineral products (2.8%), electrical machinery & apparatus (2.6%), textiles & clothing (2.3%) and telecommunication, medical & optical equipment (1.0%) (Statistics South Africa, 2023).

The manufacturing sector is spread across all provinces. Gauteng has the highest concentration of businesses at 41.6%, followed by Western Cape at 18.4%, KwaZulu-

Natal (17.7%) and the rest of the provinces comprising the other 22.3% - Eastern Cape (8.7%), Free State (5.2%), Mpumalanga (3.7%), North West (2.2%), Limpopo (1.7%) and Northern Cape (0.8%) (Statistics South Africa, 2023).

5.5.2 Target population and unit of analysis

A population refers to the entire group that must be investigated in order to collect the necessary data with the target population used to select the sample, which assists in drawing conclusions about the population. For the purposes of a research study, a population can include categories of people who have been classified in a variety of ways. The target population of the present study consisted of manufacturing firms in South Africa. Dun and Bradstreet (2022) reported that just over 162,000 manufacturing firms in South Africa are spread across all the provinces, constituting small, medium, and large firms that are either local or multinational. The unit of analysis is the most important component of any methodology because it determines the object of the enquiry, which is 'who' or 'what' is being analysed (Damşa & Jornet, 2021). Zikmund et al. (2010) posited that the unit of analysis could be individual, group, firm, community, or artefacts. In the present study, the unit of analysis consisted of firms represented by firm representatives. Barquero et al. (2019) argued that in a study, the unit of analysis is more than just the methodological focus; it also plays an important conceptual role, especially in the formulation of the research problem. To be more exact, the unit of analysis refers to the entity that the data collected describes and on which the analysis is performed. It is what the data are about to answer the research topic, and it establishes the bounds of what is studied or ignored inside the study.

5.5.3 Sampling method and techniques

The biggest challenge of fieldwork is choosing and obtaining a random sample based on the probability sampling method of the target population from which to extrapolate the results of the study. In real life, the task is so hard that almost all studies have some sampling bias to a lesser or greater degree (Banerjee & Chaudhury, 2010). In the present study, it was not possible to apply probability methods and achieve random sampling due to the incompleteness of the database and the difficulty of accessing some of the manufacturing firms, which was the same challenge encountered by the experts.

For the experts, the non-probability sampling and judgment sampling techniques were used to sample these participants (Blumberg et al., 2014), while for the firm survey, it was a convenience sampling technique. Convenience sampling remains feasible despite its limitations regarding a high level of generalisability due to its practicality and response to constraints, such as time and resource limitations, which make probability sampling less feasible. To minimise the bias of convenience sampling, researchers should know something about the population from which the sample was taken. This is important because it helps to decide if the results of a study can be applied to a larger group of people. Multistage non-probability sampling was found to be effective in improving the generalisability of the study, and this was the approach that was applied to this study. This is because it may be more practical to draw the requisite number of participants in a series of stages instead of simultaneously (Banerjee & Chaudhury, 2010). The study targeted individual firms in the manufacturing sector, both local and multinational. The sample for the research was proportionally based on the industry size and province (Statistics South Africa, 2023).

5.5.4 Ethical considerations of the research

The research adhered to required ethical considerations using the guidelines from the Ethics Committee and other considerations with research involving human interaction (Leedy & Ormrod, 2023). The research obtained ethical clearance approval based on human interaction, which should follow the required ethical considerations using the guidelines of the Rhodes University Human Research Ethics Committee (RU-HREC), approval number 2023-7527-8189 (Appendix A).

The research ensured that all the participants were informed of the study's objectives, that their participation was voluntary, and the participants had the right to discontinue their participation in the study at any time during the research. The researcher obtained consent from the participants, either written or online, by signing an informed consent form. The experts confirmed participation through communication by email, while for the survey, the first question confirmed their willingness to participate, only allowing participants who agreed to participate in the survey to continue to do so, and those who did not agree were exited from the survey. The participants were informed as to their guaranteed privacy, with no identifiers included in the final report. The data of the study participants were secured in cloud-based computing with password protection, ensuring

limited access to only authorised personnel. Contact details were provided to the participants for the different data collection tools for any inquiries and reporting of any problems encountered during their participation. Firms were sent an access letter requesting permission to conduct research.

5.5.5 Sample size and characteristics

Often, a sampling approach is required because it is not always possible to collect data from every population unit. Determining an adequate sample size is important for deriving valid conclusions from research results (Memon et al., 2020)

5.5.5.1 Expert assessment

Determining the optimal sample size for expert assessments within a complex decision-making context involves balancing precision, reliability, and practical constraints. The optimal sample size is crucial for ensuring that the conclusions drawn from expert assessments are both statistically and practically significant. This involves considering various factors such as the precision of estimations, the accuracy of distribution approximations, and the context-specific requirements of the decision-making process. A pragmatic rule is suggested for determining the optimal sample size. This involves considering both statistical and practical significance, which can vary depending on the complexity of the task and the expertise required (Crispen & Hoffman, 2016). Additionally, for the decision, it is critical that the sample size is not too large as the decision becomes unrealistic, and this can introduce a high degree of inconsistency (Pun & Hui, 2001). This means that there must be a good balance. In this study, the empirical data from the expert assessment was used from fuzzy-DEAMTEL, Kendall's W coefficient of concordance and ranking of technologies.

The sample size in multicriteria decision-making (MDCD) such as fuzzy-DEMATEL ranges from six, as described by Tarei et al. (2021), to 40. Saraswathi (2019) argued that the number of experts involved can significantly impact the reliability and validity of the results. These experts must be adequate to provide a more comprehensive view while reducing bias and increasing the robustness of the decision-making process. As such, this study targeted 20 – 30 experts. The total number of participants was 22, which was within this target range.

The evaluation was conducted by 22 experts with relevant experience in operations management, especially manufacturing, from academia, industry, consultancy, and other related areas. The experts for this research were selected based on their competence and experience. These experts were expected to have had at least ten years of experience in academia, industry, or both, which is a requisite for an acceptable expert (Abdullah et al., 2023)

Table 5.2 provides a summary of experts' professional backgrounds across various industries, their operating areas, years of experience, qualifications, functions, and roles. From the biographic information, it is evident that these experts come from various manufacturing industries, including automotive, food and beverage, metals, machinery and equipment, chemical products, wood products, petroleum, textiles, and clothing. Specific sectors like metals and metal products and automotive appear multiple times, highlighting the significance of these sectors within the expert pool. In addition, there are experts from consultancy, academia, and policy-making. These experts are consultants or academics, providing strategic advice or lecturing in fields relevant to manufacturing, operations, and management. Academia-focused experts lecture in specialised areas such as process control, operations management, and systems analysis.

These roles help disseminate knowledge to the next generation and incorporate industry insights into academic programmes. The experts' experience ranged from 11-15 years to more than 25 years. This variance indicates both depth and diversity in perspectives. The majority of the experts had 16 to 25 years of experience. The experts' extensive experience positions them well to provide expert assessment in the present research. A few experts have 11-15 years of experience, mainly in consultancy, academia, and production roles in industries like automotive and textiles. They bring a blend of fresh insights and well-rounded operational knowledge. Many experts, especially those in engineering and production fields, have technical degrees (e.g., BEng, MEng, PhD in Science, and Chemical Engineering), underscoring their expertise in industry-specific knowledge. This is mainly blended with postgraduate degrees, with several having MBAs, demonstrating a solid foundation in business management. There were some experts with advanced degrees, PhD, and DBA.

Table 5.2: Bibliographic information of experts in the study

Expert	Operating area	Experience	Highest qualification	Function	Role
Expert 1	Management Consultancy and Advisory	More than 25 years	Postgraduate - MBA in Financial management	Strategic / General management and IT and/or technology	Senior / Executive Management – Director Lead in Smart Manufacturing
Expert 2	Industry – Automotive	11 – 15 years	Postgraduate – Management, undergraduate - Industrial Engineering. Finishing MBA	Production Management and previous Maintenance Manager (Integrated Technology) and Contracts Management Specialist	Middle management Engineering and previously in quality assurance
Expert 3	Industry – Food and Beverage	16 – 25 years	Postgraduate – MBA, undergraduate – Management & Operations	Production Management	Middle management in production management
Expert 4	Industry - Metals and metal products	16 – 25 years	Ph.D. in Science and MBL	Strategic / General management - Technical Advisor previous Production Management	Senior / Executive Management - Lead Process Engineer
Expert 5	Industry - Metals and metal products	16 – 25 years	Master's in Engineering, MBL	Production and Quality previous Technical and World Class world Practice Management	Senior / Executive Management - Laboratories Manager previous Production Engineering Manager
Expert 6	Machinery and equipment	16 – 25 years	Masters in Engineering and MPhil in Business Management Corporate Strategy	Senior / Executive management	Senior / Executive Management -Managing director, previously Head of Site QHSE & Information System, and quality control manager

Expert	Operating area	Experience	Highest qualification	Function	Role
Expert 7	Industry – Food and Beverage	16 – 25 years	PhD	Lecturer / Senior Lecturer previously Senior / Executive management	Lecturing - Teaching process control and systems analysis, previous Quality Assurance Manager, Product and technology development
Expert 8	Automotive industry	More than 25 years	Technical degree and MBL	Strategic / General Management and Production and supply chain	Supply chain senior manager, previously technical manager
Expert 9	Wood and wood products	More than 25 years	MBA	Strategic / General management	Senior / Executive Management - General Manager
Expert 10	Consultancy	11 – 15 years	MSc, MBA	Strategic / General management	Senior / Executive management
Expert 11	Chemical Products	16 – 25 years	M Eng Chemical Engineering, PGDip Management	Production	Senior / Executive management – Senior Production Manager
Expert 12	Petroleum, chemical products	16 – 25 years	B Eng Industrial Engineering	Marketing and Sales, previously contract manager	Sales and Marketing executive previously Contracts specialists and Business Analyst
Expert 13	Policymakers	16 – 25 years	MBA, MCom	Policy Development and implementation	Senior / Executive Management – Director
Expert 14	Consultancy	11 – 15 years	BTech, PGDip, MBA	Strategic / General management	Middle management - Specialist
Expert 15	Consultancy	16 – 25 years	BSc Hons MDP (Postgraduate Diploma)	Strategic / General management	Senior / Executive management – Owner and Director
Expert 16	Consultancy	16 – 25 years	MCom, MBL	Strategic / General management	Specialist - Senior Associate
Expert 17	Consultancy	More than 25 years	MSc, Postgraduate Diploma in Business Management	Strategic / General management	Senior / Executive Management – Executive Director

Expert	Operating area	Experience	Highest qualification	Function	Role
Expert 18	Academia	11 – 15 years	PhD (Science)	Lecturer / Senior Lecturer, previously technical manager	Senior Lecturer previously Taught operations management and Senior / Executive management
Expert 19	Academia	16 – 25 years	MCom, DBA	Lecturer / Senior Lecturer Previously supply chain and contracts manager	Teaches Operations management and supply chain. previously Senior / Executive management
Expert 20	Textiles and clothing	16 – 25 years	B Eng, M Eng	Production previously quality	General manager manufacturing
Expert 21	Textiles and clothing	11 – 15 years	BSc, PGDip, MBA	Production	Senior / Executive Management -Production Manager
Expert 22	Industry - Metals and metal products	More than 25 years	B Eng Chemical Engineering, PGDip in Management	Production	Middle management - Technical Manager

MBA – Master(s) in Business Administration; MBL – Master of Business Leadership; PhD – Doctor of Philosophy; MPhil – Master of Philosophy

Source: Author

Most of these experts work in strategic or general management roles, overseeing large-scale decisions impacting the organisation's direction. Experts in consulting contribute to strategic decision-making by providing insights on operations, production, and management trends. Executive management in the automotive and food and beverage industries also plays crucial roles in aligning production strategies with business objectives. Several experts manage production within their industries and handle daily operations, resource allocation, and quality control. The majority of experts hold senior or executive-level positions, indicating that they are influential decision-makers within their organisations. This level of leadership includes roles like Director, Senior Production Manager, General Manager, and Managing Director

5.5.5.2 Firm survey

The firm survey data were collected for PLS-SEM (Kono & Sato, 2023; Melo-Mariano & Plá, 2023) and fsQCA (Ragin, 2009) analysis. Although there are several commonly accepted rules of thumb for calculating sample size, researchers are uncertain as to which one to use for selecting sample size for their individual studies.

The majority of research advocates a minimum sample size of 100 for a predictive model for PLS-SEM, although recently, authors such as Jhantasana, (2023) advanced a minimum of 50 to achieve a statistical power of 0.80. To ensure the adequacy of the sample, the sample size was determined using the equation by Cochran (1977):

$$n = \frac{Z^2 P(1 - P)}{d^2} \quad (1)$$

where n = sample size, and Z statistic (Z) = 1.96 represents confidence level. P is the expected proportion (in proportion to one; if 50%, $P = 0.5$), while d is the precision. In proportion of one, if 5%, $d = 0.05$, the sample size is 384. A total of 262 respondents participated in the survey, which equated to a response rate of 68.3%. This was an acceptable response rate because not only was it better than the response rate of 33% for the online survey, but it was an increase over the 60% for the manual survey by Nulty (2008). It was also better than the 60% advocated by Wu et al. (2022).

In addition, it has achieved the minimum responses required to develop a structural equation model. Based on the multistage non-probability sampling to reduce bias, the sampling included coke, petroleum, chemical products, food products and beverages,

transport equipment, metals, metal products, machinery and equipment, and Others. The “Others” included * wood, wood products, paper, publishing and printing, furniture and other manufacturing, glass and other non-metallic mineral products, electrical machinery and apparatus, textiles and clothing and telecommunication, medical and optical equipment. These industries are indicated in Table 5.3.

The simple deviation of the actual from the target sample was calculated, and there was no major deviation between the targeted sample in an industry (T) and the actual sample (A), with the highest being metals, metal products, machinery, and equipment slightly higher than the target. An attempt was also made to ensure a footprint in each province, with a minimum sample of ten participants for any province. This was done so that each province had some representation. This was achieved by adjusting down from the three biggest provinces of Gauteng, Western Cape and Kwa-Zulu Natal. The deviation was also low except for North-West Province, where more samples were collected compared to the target.

The achievement of the minimum required sample size for PLS-SEM and fsQCA, use of multistage sampling approach and the triangulation of data from multiple methods and sample from experts and firm representatives mitigates potential bias in the study's analyses

Table 5.3: Characteristics of the sample

	Size Proportion (Income) – Target (T)** (%)	Size based on Actual (A)# (%)	$ D = T - A $	Province	Size Proportion (Province) - Target (T)**	Size based on actual (A)#	$ D = T - A $
Coke, petroleum, chemical products	25.8%	22.1%	3.7	Gauteng	40.0	37.2	2.8
Food products and beverages	22.6%	23.7%	1.1	Western Cape	17.6%,	14.8%	2.8
Transport equipment	17.1%	17.6%	0.5	KwaZulu-Natal	17.0%	14.5%	2.5
Metals, metal products, machinery & equipment	16.3%	20.6%	4.3	Eastern Cape	8.7%	6.9%	1.8
Others*	18.2%	16.0%	2.2	Free State	5.2%	4.6%	0.6
				Mpumalanga	3.7%	2.7%	1.0
				Northwest	2.6%	13.7%	11.1
				Limpopo	2.6%	3.1%	0.5
				Northern Cape	2.6%	2.7%	0.1

* Wood, wood products, paper, publishing and printing, Furniture and other manufacturing, Glass and other non-metallic mineral products, Electrical machinery and apparatus, Textiles and clothing and Telecommunication, medical and optical equipment.

** - Target sample = 384 # – Actual = 262 – Response rate = 68.2%

Source: Author

The demographic information for the participants is provided for both the firm survey responses and experts. Demographic information provides the necessary insights into population and sample characteristics. The demographic information of the participants in the firm survey is presented in Table 5.4.

Table 5.4: Demographic information from business firm survey

Biographic information variable		N	%
Province	Eastern Cape	18	6.87
	Free State	12	4.58
	Gauteng	97	37.0
	KwaZulu Natal	38	14.5
	Limpopo	8	3.05
	Mpumalanga	7	2.67
	Northwest	36	13.7
	Northern Cape	7	2.67
	Western Cape	39	14.9
Industry	Coke, petroleum, chemical products, rubber, plastic	58	22.1
	Food & beverage	62	23.7
	Transport equipment	46	17.6
	Metal, metal products, machinery & equipment	54	20.6
	Others	42	16.0
Firm size (Revenue)	Less than R35m	43	16.4
	R35m - R90m	62	23.7
	R91m - R357m	48	18.3
	More than R357m	109	41.6
Employee numbers	1- 50	45	17.2
	51 - 250	56	21.4
	251 - 1000	60	22.9
	1001 - 5000	54	20.6
	More than 5000	47	17.9

Source: Author

These data included information on the characteristics of the province, industry, the size of the firm, and the number of employees. Gauteng had the largest representation

(37.0%), followed by the Western Cape (14.9%) and KwaZulu-Natal (14.5%). These provinces constituted two-thirds of the responses (66.4%). This is followed by representations of the Northwest (13.7%), the Eastern Cape (6.87%), and the Free State (4.58%).

Food and beverage is the largest industry segment, accounting for 23.7% of total responses. Other significant industries include Coke, Petroleum, Chemical Products, Rubber and Plastic (22.1%) and Metal, Metal Products, Machinery and Equipment (20.6%). Transport Equipment also has notable representation (17.6%), while Other Industries - Wood, wood products, paper, publishing & printing; Furniture other manufacturing; Glass other non-metallic mineral products; Electrical machinery & apparatus; Textiles& clothing; Telecommunication; Medical & optical equipment, accounts for the remaining 16.0%.

The firm size was based on the Department of Trade Industry and Competition's (DTIC) 2003 cut-off points, which are adjusted by a factor of 7 by Statistics South Africa (2023) for the size group cut-off points. The firms that participated were large firms with revenues of more than R357m (41.6%). This was followed by firms with revenues R35m - R90m (23.7%) and R91m - R357m (18.3%), with smaller ones (less than R35m) also well represented with 16.4%. The firm with 251-1000 employees was the largest group (22.9%), followed by those with 51-250 employees (21.4%) and 1001-5000 employees (20.6%). Smaller and larger firms, 1-50 employees and more than 5000 employees account for 17.2% and 17.9%, respectively.

5.5.6 Instrument

5.5.6.1 Experts' assessment

An expert assessment guide was part of the empirical data collection. Expert scientific judgment entails making well-thought-out judgments and decisions rooted in extensive knowledge and skills (Brownstein et al., 2019). The instrument comprised four sections of questions. The first section validated the relevance of the expert (Guetterman, 2015) based on the area of operation in the sector, which could be an industry, consultancy, academia, or policy-makers or implementers. There was also an interest in the years of experience in that sector(s), with the qualifier being a minimum of 5 years – 10 years. There was also an interest in the operating field, which could be in strategic/general

management, production, it and/or technology, marketing and sales, academia, or others. In addition, information was sought on their role and education, with roles being either senior/executive management, middle management, junior management or supervisor, specialist, lecturer, senior lecturer, associate professor, or professor.

The second section focused on operational uncertainty with a pairwise determination of the row's influence on the column, where the expert used a 5-point Likert scale (Likert, 1932) ranging from 1- No influence 2 – Very low influence 3 –Low influence 4 – High influence 5 – Very high influence. The following section focused on the impact of operational uncertainty in manufacturing also using a 5-point Likert scale ranging from 1- Insignificant (Minimal impact), 2 – Minor (Short-term impact), 3 –Moderate (Significant impact), 4 – Major (Major short-term impact) 5 – Severe (Major long-term impact). (drop down). The last section focused on the Fourth and Fifth Industrial Revolution technologies. The interest was for the expert to determine the best technology for the required manufacturing capability using a 3-point scale: 0 = Incapable; 1 = Partially capable; 2 = Fully capable. The complete instrument is provided in Appendix B.

5.5.6.2 Survey of business firms

The firm survey was developed using a questionnaire that included sections on demographic information, operational uncertainty dimensions, Industry 4.0 and 5.0 technologies in use in the firm and their capabilities, organisational learning and sustained performance.

The demographic information included the province where the manufacturing firm was located, the industry within the manufacturing sector, and the size and number of employees. The operational uncertainty dimensions assessed were geopolitical tension (GPT), policy and regulatory uncertainty (PRU), Cost-of-living-driven consumer behavioural change (CLC), pandemic turbulence (PDT), and energy stability and security (ESS). Additionally, there were skills for future industrial work (SFW) and the entrenchment power of large firms (EPL), generational work behaviour and ethics (GWB) and process capability and variations (PCV). Each dimension was treated as a latent construct, and four items were used to measure it. This used a 5-point Likert Scale to assess the degree of agreement and disagreement with each item's statement. In this study, the Likert scale used was symmetrical and balanced, even though there are other designs with

measurement ranges ranging from two to eleven points, depending on the number of response alternatives (Simms et al., 2019).

The next section sought to understand the Industry 4.0 and 5.0 technologies that were currently in use in the firm. In addition, study participants could also add other technologies that are not on the questionnaire list. This was followed by a section on the state of organisational learning, which used a 5-point Likert scale (Strongly disagree = SD, Disagree = D, Neither disagree nor agree = N, Agree = A, Strongly agree = SA). The last section was on sustained performance, where the study participants ranked their firm based on its performance over the past 3 years. This ranking utilised a continuous scale of 1 - 10, with a low score such as 1 indicating very negative outcomes (change), progressing to 5 = no change, then towards 10 = very positive outcomes (change). The full instrument is provided in Appendix C.

5.5.7 Data gathering methods

The expert assessment and the survey were conducted in a hybrid form—online and face-to-face, with the online assessment using SurveyMonkey®. Each expert had an opportunity to set up a meeting with the researcher to explain the study to them. A short video was also made to explain the study. This video is now posted with the link: https://youtu.be/gJc9DVbySks?si=jVcsOeSo5Y6_PR3c. For the expert assessment and firm survey, the link for online submission and manual survey questionnaires were distributed via email and other social media platforms, such as LinkedIn. Both the expert assessment and firm survey were self-administered. The data were collected over nine months, from December 2023 to September 2024.

5.6 Data analysis methods and models

5.6.1 Data Preparation

The collected survey data were imported to IBM Statistical Package for Social Science version 29, where descriptive and inferential statistics were used to analyse the data. Initially, the data were coded, then screened and cleaned, ensuring no issues with non-response bias (Berg, 2005; Groves & Lyberg, 2010) extreme outliers (Schwertman et al., 2004), missing values (Dong & Peng, 2013) common method variance (Fuller et al., 2016), and normality distribution of the empirical data.

5.6.1.1 Missing value analysis

This was followed by evaluating the missing values. (Schafer, 1999) proposed a threshold of 5%, while Dong and Peng (2013) suggested a threshold of 10%. Missing data can be missing at random (MAR), missing fully at random (MCAR), or missing not at random (MNAR), as described by (Rubin, 1976). To comprehend the mechanisms behind the absence of desired data, Little's MCAR test was conducted to determine if the missing values were at random with a significance of more than 5% ($p < .05$), confirming that the missing values were at random.

5.6.1.2 Non-response bias

Measurement errors tend to be the main source of bias in the survey's empirical data (Celhay et al., 2022). Groves and Lyberg (2010) argued that non-response is one of the major measurement errors. The data collected were analysed to identify potential bias in the sample. The research assessed the bias between early and late respondents for non-response bias, normally conducted using chi-square tests (Armstrong & Overton, 1977) or an independent sample t-test (Af Wählberg & Poom, 2015). This research employed the independent sample t-test to investigate the non-response bias.

$$t = \frac{\bar{X}_e - \bar{X}_l}{\sqrt{\frac{S_e^2}{n_e} + \frac{S_l^2}{n_l}}} \quad (2)$$

where $\bar{X}_e$ and $\bar{X}_l$ are the means of early (Dec 2023 -April 2024) and late (May -September 2024) responses, S_e^2 and S_l^2 are variances of the groups, while n_e and n_l are sample sizes of the groups.

In addition, an effect size analysis was also computed. Effect size is important in providing the complete picture as sometimes statistical significance between the groups can result even when there is a trivial difference. Groups with Cohen's d of < 0.20 are regarded as having a very small effect (Cohen, 1988). Cohen's d effect size formula is:

$$d_s = \frac{\bar{X}_e - \bar{X}_l}{T_p} \quad (3)$$

where T_p is the pooled standard deviation.

The results demonstrated that more than an 80% threshold was achieved for indicators that were not statistically significant and/or had a small effect size of less than 0.20. This indicated that there were no notable disparities and statistically significant changes, implying that the dataset and model developed were not affected by non-response bias. As such, the data were used as one segment. To ensure robustness, the data were later subjected to finite mixture (FIMIX) segmentation to uncover latent segments in the data.

5.6.1.3 Extreme outliers

The extreme outliers in the firm survey empirical data were assessed using the box-plot-based method (Schwertman et al., 2004). The boxplots use the interquartile range (IQR) to identify outliers, marking data points outside 1.5 times the IQR as potential outliers. The external validity of a study can be compromised if outlier cases are not properly detected and treated (Carter et al., 2009). Parametric statistics rely heavily on the assumption of normal distribution, which outliers can violate. An influential outlier example is one that significantly alters the distribution's mean or standard deviation. Errors in data collection or entry may account for the existence of outliers. They could also be legitimate outliers among the intended demographics. Regardless of their origin, outliers require special treatment before data analysis to mitigate their possible impact on generalisability. Identifying, categorising, and dealing with outlier cases can be accomplished using a number of different statistical methods. This study offered a high-level conceptual overview of the methods currently used to detect and handle univariate outliers (Mowbray et al., 2019). In this research using SPSS, the extreme outliers are data set points that are at 3 times the interquartile range (3 X IQR) or higher. Although there were some indicators with outliers at 1.5X IQR, there were no indicators with extreme outliers. The boxplot of the variables is provided in Appendix D.

5.6.1.4 Common method variance

The Harman one-factor test was used to detect the common method variance (Fuller et al., 2016). In Harman's single-factor test, the percentage of variance that is connected to the first component (or factor), the one that refers to the greatest eigenvalue, is tested against a threshold of 0.5. This helps to determine whether or not the component in question is significant. This percentage is sometimes referred to as the "total variance explained" by the first component (or factor) retrieved during the analysis process. Users of the test may become confused as a result of this, as it may give the impression that it

is the total variance in the latent variable that is explained by the indicators when, in reality, it is 1 (one hundred percent) for the first component. For the corresponding factor, it equals the factor's reliability (Kock & Govender, 2021). Harman's single-factor test for detecting common method bias was conducted to rule out that a single factor may account for most of the variance, with expected results of less than 50% for acceptable levels (Aguirre-Urreta & Hu, 2019). In the present research, Harman's single-factor test was conducted with principal axis factoring, with the total variance extracted being 11.67%, which is better than the threshold of 50%. As such, there were no issues with CMV in the data (Jordan & Troth, 2020).

5.6.1.5 Normality distribution

Skewness and kurtosis assess the normality assumptions in statistical analysis, as they provide insights into the shape and tails of a distribution (Hattem et al., 2022). Skewness measures asymmetry, while kurtosis assesses a distribution's peakedness or tail heaviness. Deviations from normality, indicated by non-zero skewness and kurtosis, can significantly impact statistical analyses, particularly those relying on the assumption of normality. Skewness and kurtosis were also analysed. The idea behind skewness and kurtosis is based on distribution. A measure of how symmetrical a distribution is can be found in skewness. In a nutshell, if the distribution curve is symmetric, it appears the same from either side of the point upon which it is centred. It is stated to have an unbalanced or skewed perspective when this is not the case. Outliers are represented by kurtosis in statistical analysis. Distributions that have a high kurtosis tend to have "heavy tails," which indicates a greater number of outliers, whereas distributions that have a low kurtosis tend to have light tails, which indicates that there are fewer outliers (Kaliyadan & Kulkarni, 2019). The data have heavy tails if they have a high kurtosis value, and this type of kurtosis is known as leptokurtic kurtosis. On the other hand, kurtosis, which is characterised by the opposite situation, is known as platykurtic kurtosis.

There is some disagreement between the authors as to the threshold for the skewness and kurtosis, with some being as conservative as ± 1 for both skewness and kurtosis, while others varying between ± 2 for skewness and up to ± 7 for kurtosis. George and Mallery (2010) suggested ± 2 as being considered acceptable to prove normal univariate distribution. Hair et al. (2010) posited that the data are normally or near normally distributed if skewness is ± 2 and ± 7 for kurtosis, while others, such as Yuan et al.,

(2005), recommended ± 5 for kurtosis. Skewness and kurtosis for the present study were within ± 2 and ± 5 . Details are provided with the relevant descriptive statistics in Chapters 6 to 8. Although this test was not as sensitive as the Shapiro-Wilk Test, it was sufficient for this research as the main analytical method, Chi-Square, structural equation modelling partial Least square (PL-SEM) and fsQCA do not require to meet the normality assumption.

5.6.2 Descriptive statistics

The demographic profile of the firms was analysed using frequency and percent frequency. Descriptive statistics analysis was then followed to determine the data's central tendency and dispersion. The mean, median and mode are the three common measures for central tendency. The mean is the most common and standard method for determining the central tendency of a set of data (Jaggers & Loomis, 2020). It is also widely believed to be the most accurate. Nevertheless, there are some circumstances in which one of the other measures of central tendency might be more appropriate. Median is recommended when data are measured on an ordinal scale, and mode is preferred when data are measured on a nominal scale. Reporting the median in addition to the mean is ideal as it is more robust, and outliers or skewed empirical data do not influence it, and it can be determined for different measurement scales such as ordinal, interval, and ratio. When all the observations were sorted in an ascending or descending sequence, the value that represents the median is the one that falls in the middle. It does so in an accurate manner, creating two halves out of the frequency distribution. In a distribution, fifty percent of the observations have scores that are equal to or lower than the median. Therefore, the median corresponds to the 50th percentile. Dispersion was measured in a number of different ways, including the standard deviation, standard error, and confidence interval.

5.6.3 Statistical methods and models for testing propositions

The statistical method and models were based on the propositions of the research. This was viewed as a logical approach, allowing for an effective direct connection of each analysis with a specific research proposition. This approach helps to show a clear alignment between the propositions and analytical methods and, in later chapters, the results. The statistical analysis was conducted with SmartPLS version 4 (Ringle et al., 2024) and fsQCA 4.1 (Ragin & Davey, 2022).

5.6.4 Multidimensionality of the operational uncertainty

Proposition one, that operational uncertainty is a multi-dimensional construct, was investigated by adapting and expanding the 3-step process (Define – Operationalise – Confirm) by (Lambert & Newman, 2023)

In step 1 – Construct conceptualisation and definition, the literature was reviewed, and the nine theoretical dimensions (GPT, PRU, CLC, PDT, ESS, GWB, SFW, EPL, and PCV) of operational uncertainty, as detailed in Chapter 3.

Step 2 – Operatise the construct, which was conducted by generating the indicators and accessing content validity by seeking the view of five experts who provided input and which were incorporated in the final instrument.

Step 3 – Confirm construct validity was done by collecting the empirical data from the manufacturing firms, and these data were tested with a scatter plot, corrected item-total correlation, measurement model of dimensions and exploratory development of the higher-order construct (HOC), operational uncertainty.

5.6.4.1 Scatter plot

Initially, the data for the dimensions of the operational uncertainty were analysed with a scatter plot to determine the correlation patterns. Nguyen et al. (2020) explained that scatter matrix plots are used to show statistical graphics and expose patterns in multivariate data, as is the case in this research.

5.6.4.2 Corrected Item-Total Correlation

Corrected item-total correlation was analysed because it is useful in scale development and assessment (Zijlmans et al., 2018). It assesses how well each of the scale's indicators contributes to the overall measurement of the construct—operational uncertainty. This assessment is useful in identifying indicators that may not perform well within a scale. Simply put, it is to understand whether an item aligns with the measured overall construct. An item with a low item-total correlation may not fit well with the others. This is calculated with the following equation.

$$r_{i,(t-i)} = \frac{\sum (X_i - \bar{X}_i)(T - X_i - \bar{T}_{-i})}{\sqrt{\sum (X_i - \bar{X}_i)^2 \cdot \sum (T - X_i - \bar{T}_{-i})^2}} \quad (4)$$

where X_i is the score for the indicator, T is the total score based on the sum of all indicators in the scale, $T - X_i$ is the total score excluding the indicator, while $\bar{X}_i$ is the mean indicator and $\bar{T}_{-1}$ is the mean of the total score excluding the indicator being measured. A value of 0.3 indicates an acceptable level of corrected item-total correlation (Pallant, 2020).

5.6.5 Measurement model

Confirmatory factor analysis was performed using the structural equation modelling partial least squares (PLS-SEM) to produce a measurement model for both the lower-order and higher-order constructs.

5.6.5.1 Confirmatory tetrad analysis

Confirmatory tetrad analysis (CTA) was used to analyse the format of the model analysis. Understanding these models' differences and appropriate applications is crucial for accurate data analysis and interpretation in PLS-SEM (Hair et al., 2019). The distinction between the reflective and formative has significant implications for model specification, assessment, and interpretation in PLS-SEM (Hanafiah, 2020). The assessment is conducted with confirmatory tetrad analysis (CTA) (Gudergan et al., 2008). The tetrad analysis is formulated as follows:

$$\tau_{1,2,3,4} = cov(1,2) * cov(3,4) - cov(1,3) * cov(2,4) \quad (5)$$

where cov is the covariance, the tetrad analysis works on a minimum of four indicators for each dimension. The tetrad is the difference between the product of one pair of covariances and the product of another pair of covariances. By considering the tetrads, researchers can understand the relationship between pairs of covariances.

5.6.5.2 Composite reliability and reliability

The composite reliability was then assessed to measure the internal consistency of the scale items. The sum of squares of entirely standardised factor loadings divided by this sum plus the total variance of the error term for i th indicators yields the CR for each construct. The CR may be computed as:

$$CR = \frac{\sum_{i=1}^n \lambda_i^2}{\sum_{i=1}^n \lambda_i^2 + \sum_{i=1}^n var(\varepsilon_i)} \quad (6)$$

where n is the number of items, while λ_i the factor loading for the items, i , $var(\varepsilon_i)$ is the variance of the error of the item i .

5.6.5.3 Convergence validity

The convergent validity measures the degree of correlation between multiple indicators of the same construct that agree and was assessed using the average variance extracted (AVE) equation as follows:

$$AVE = \frac{\sum_{i=1}^n \lambda_i^2}{n} \quad (7)$$

where λ are the factor loadings while n are the indicators in the factor. The AVE should be 0.5 or higher to confirm convergence validity.

5.6.5.4 Discriminant validity

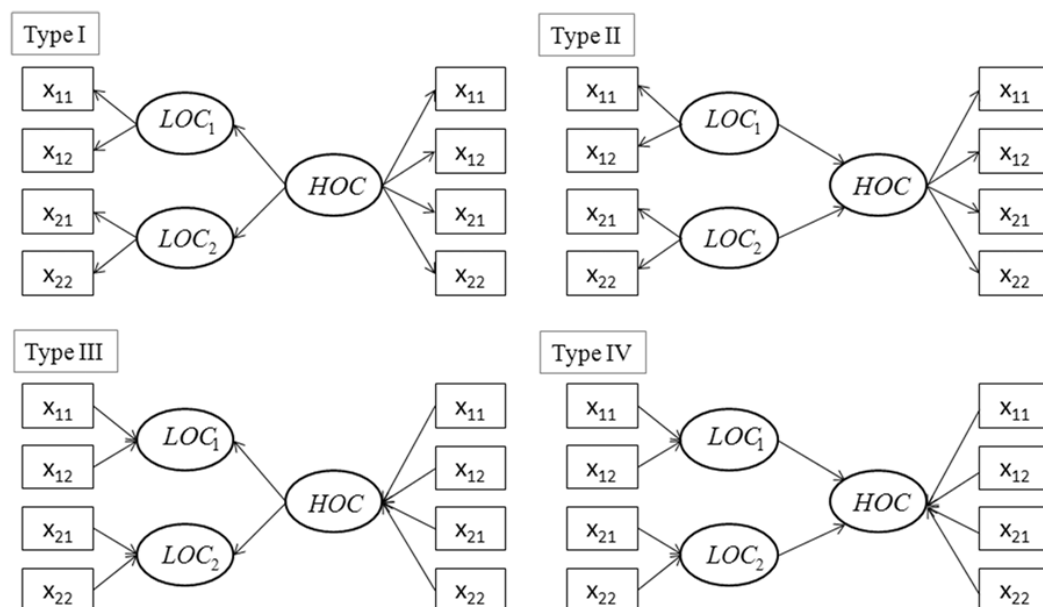
Multiple methods were used to conduct discriminant validity in this research. Each method has its strengths and limitations, and using them in conjunction can offer a more robust discriminant validity assessment (Rönkkö & Cho, 2022). These were the Fornell-Larcker Criterion (Fornell & Larcker, 1981), cross-loadings, and the Heterotrait-Monotrait criterion (HTMT) (Henseler et al., 2015). A method that involves comparing the square root of the Average Variance Extracted (AVE) of each construct with the correlations between the construct and other constructs in the model. A construct should have a higher square root of AVE than its correlation with any other construct to establish discriminant validity (Henseler et al., 2015). This means that the diagonal values represent the square root of the AVE for each dimension, and the off-diagonal values represent the correlations between dimensions. Cross-loading assesses whether an indicator's loading on its assigned target dimension is higher and should be higher than its cross-loadings on other factors. The Heterotrait-Monotrait criterion (HTMT) determined the discriminant validity analysis (Henseler et al., 2015):

$$HTMT_{ij} = \frac{W}{\sqrt{R \times Q}} \quad (8)$$

where W is the average of all pairwise correlations between items of the first construct and the second construct; R is the average monotrait-heteromethod correlations, which are means of all pairwise correlations between items of the first construct, and Q is the average monotrait-heteromethod correlation which is all pairwise correlation between items of the second construct. The recommended threshold considered in this study was 0.85 ($H_{.85}$) (Kline, 2011) and a less conservative of 0.90 ($H_{.90}$) (Henseler et al., 2015).

5.6.5.5 Exploratory development of HOC

The higher-order construct (HOC) was conducted using a disjoint two-stage approach (Crocetta et al., 2021; Sarstedt et al., 2019). It used the PLS-SEM measurement model (LOC and HOC) for causal dimensions with sustained performance. The measurement model for LOC was conducted similarly to section 5.6.1.3 Measurement model. The analysis in HOC examines the multiple relationships among various blocks of Manifest Variables (MV), positing that each block is represented by a Latent Variable (LV) or a theoretical concept. The relationships between these blocks are grounded in the theoretical understanding of the analysed phenomenon (Crocetta et al., 2021; Sarstedt et al., 2019). The study categorised the HOC as either a reflective-reflective, reflective-formative, formative-reflective, or formative-formative model (Figure 5.2).



Note: Type I – Reflective-reflective, Type II - Reflective-Formative, Type III – Formative -Reflective, Type IV- Formative-Formative.

Figure 5.2: Types of higher-order model

Source: Crocetta et al. (2021).

Each category specifies the distinct relationship between higher-order constructs (HOC) and lower-order constructs (LOC), which in this study are the causal dimensions of operational uncertainty, along with the measurement technique utilised for the LOCs. The LOC and HOC were analysed for validity and reliability in a similar manner, as described in earlier in this section.

5.6.6 Level of uncertainty

Proposition two, that operational uncertainty is a norm in the manufacturing sector, was tested using a relative importance index (RII) for the individual dimensions and a composite score for operational uncertainty for the overall levels.

5.6.6.1 Relative Importance Index

The relative importance index (RII) was analysed to understand the ranking of importance or high impact of operational uncertainty using the 5-point Likert scale. This used the following equation:

$$\overline{RII} = \sum \frac{W}{A \times N} \quad (9)$$

where W = weighting given to each factor, A = highest factor and N = total number of respondents. This was done to understand the dimension of operational uncertainty perceived to bring the highest and lowest operational uncertainty.

5.6.6.2 Development of composite score of operational uncertainty

5.6.6.2.1 Notations and Assumptions

A four-step process was developed to measure the composite score of operational uncertainty. To define the operational uncertainty composite score, the notation is utilised (Table 5.5):

Table 5.5: Notations and assumptions

Decision	
α	Cronbach Alpha Coefficient for internal consistency reliability
ξ_{sj}	Uncertainty assessment factor score for the final individual factors of a firm or business unit, j .
COA_j	Composite score of the combined constructs, OAF_j
Parameters	
$\bar{a}$	Mean score of indicator
a	Individual indicators
k	Number of indicators
σ_y^2	Variance of each indicator
σ_x^2	Variance of the total score for observation
ξ	Latent variable (dimension)
λ_i	Effect of ξ on a_i
δ_i	Measures uniqueness
j	Firm or business unit
m^{max}	Maximum score of assessing the scale
$\overline{Y_{g\xi}}$	Normalised score of the dimension observation or alternative, g for factor (criterion)
ξ, Y_ξ	Actual score
Y_ξ^{max}	Maximum score from ξ, Y_ξ
Y_ξ^{min}	Minimum score from ξ, Y_ξ
s_j	Standard deviation
m	Total number of factor observations or alternatives.
ρ	Spearman's rank correlation coefficient
d_i	Difference between the two ranks of factors
P_ξ	Information content of g_j
w_j	Objective weight of Y_ξ
ξ_{sj}	Combined dimensions (constructs)

Source: Author

The assumptions used to create the composite score are as follows.

1. *Multi-dimensional construct.* Operational uncertainty is a multi-dimensional construct that is evident in the external operating environment, at the industrial level, and at the individual firm level (Sniazhko, 2019).
2. *Sample for empirical data.* The sample size must also be considered in determining the sample's credibility, which is critical for effectively validating the model's sample relevance and adequacy. Multiple approaches can be used to determine the sample size, including the central limit theorem (CLT), GPower (Mayr et al., 2007), or the inverse square root method (Kock & Hadaya, 2018). The CLT proposes a sample size of $n=30$ to $n=60$ (Islam, 2018; Zhang et al., 2023). A larger sample size tends to improve the rigour of the findings for decision-making (Lund, 2023).
3. *Operational uncertainty comprises multi-dimensional reflective dimensions* where the indicators serve to define dimensions (lower order constructs) (Christophersen & Konradt, 2012; Theodosiou et al., 2019). The approach to the index is that of a reflective model that allows an indicator to be added or excluded from the latent variable. A reflective model equation is described by Edwards (2011) as follows:

$$a_i = \lambda_i \xi + \delta_i \quad (10)$$

where the a_i is the indicator, $a_1, a_2, \dots, a_k$ k being the number of indicators. ξ is the associated latent variable, λ_i is regarded as the effect of ξ on a_i and δ_i measures uniqueness.

4. *Measurement scores.* The score highlights the level of operational uncertainty, with a low score indicating low operational uncertainty, while a high score indicates high operational uncertainty (Courtney, 2001; Walker et al., 2003).
5. *Respondents analysis.* The relevant sample should include responses from top-level strategic management, process owners, technical specialists, and consultants with pertinent experience (Mtotywa, 2022), both inside and outside the firm. Ideally, the population must reflect the sample distribution.

5.6.6.2.2 Step 1: Identification of theoretical dimensions

In research based on conceptualising the focal construct, there are two common approaches to developing indicators (Diamantopoulos & Siguaw, 2006). Either the construct can be viewed as the source of its indicators, or the indicators can be viewed as defining characteristics of the construct (Diamantopoulos & Siguaw, 2006). In the present research, dimensions were viewed as source indicators with the theory-driven method used for scale development (Spector, 2013). The theoretical or empirical dimensions are the nine-dimension discussed in Chapter 3: GPT, PRU, CLC, PDT, ESS, SFW, EPL, GWB and PCV. As explained earlier, this list of dimensions is not exhaustive, and some sources of uncertainty can be added, or existing ones can be replaced.

5.6.6.2.3 Step 2: Measurement indicators and determination of the level of individual factors

The developed analysis is focused on nine dimensions of operational uncertainty, each of which contains four indicators. Therefore, the composite score for operational uncertainty consists of 36 items that collectively focus on gaining knowledge of the level of operational uncertainty present in the firm (Appendix C). To determine the operational uncertainty of individual factors, the inter-item correlation of the individual indicators followed by Cronbach alpha for internal consistency reliability should be performed. For the Cronbach alpha, use the following equation:

$$\alpha = \frac{k}{k-1} \left(1 - \frac{\sum_{i=1}^k \sigma_y^2}{\sigma_x^2} \right) \quad (11)$$

where α is the Cronbach alpha, k is the number of indicators, σ_y^2 is the variance of each indicator, and σ_x^2 is the variance of the total score for observation.

It can be confirmed with a corrected item-total correlation. Upon confirming that the indicators are part of the dimension construct, then the individual dimensions operational uncertainty assessment score, ξ_s which is calculated for the final individual factors (GPT, PRU, CLC, PDT, ESS, SFW, EPL, GWB, and PCV) for manufacturing (which can be a firm or business unit), j , has the following equation:

$$\xi_{sj} = \frac{\sum_{i=1}^k \bar{a}_j}{k \times m^{max}} \quad (12)$$

where $\bar{a}$ is the mean score of individual indicators, $\bar{a}_{1j}, \bar{a}_{2j} \dots \bar{a}_{kj}$ with k being the number of indicators and m^{max} being the maximum score of operational uncertainty, which is five in the 5-point Likert scale. The number of indicators will be based on those present and retained in the model in the reflective model (Hanafiah, 2020).

5.6.6.2.4 Step 3: Determining the weight estimates of the factors

The next step is to determine the weight estimates of the factors using the importance of the criteria through the inter-criteria correlation (CRITIC) method with Spearman correlation. This is done by analysing the criterion, i.e., the importance of empirical factors through the inter-criteria correlation based on the standard deviation (Diakoulaki et al., 1995). This is a direct rating with an integrated additive synthesis weighting method (Odu, 2019).

This is conducted using the following steps:

- i. Normalisation of the decision matrix, which is a process of transformation of scores into a standard scale that ranges from 0 to 1. During this step, the factors are classified as beneficial or non-beneficial and calculated using the following equation for beneficial factors and the lower equation for non-beneficial factors:

$$\bar{Y}_{g\xi} = \frac{Y_{g\xi} - Y_{\xi}^{min}}{Y_{\xi}^{max} - Y_{\xi}^{min}} \quad (13)$$

$$\bar{Y}_{g\xi} = \frac{Y_{\xi}^{max} - Y_{g\xi}}{Y_{\xi}^{max} - Y_{\xi}^{min}} \quad (14)$$

where $\bar{Y}_{g\xi}$ is the normalised score of the factor observation or alternative, g for factor (criterion) ξ , Y_{ξ} is the actual score, with Y_{ξ}^{max} being the maximum score and Y_{ξ}^{min} minimum score within the indicator, observation or alternatives.

- ii. Calculate the standard deviation of each factor (criterion):

$$s_j = \sqrt{\frac{(\sum_{n=1}^m Y_{g\xi} - \bar{Y}_\xi)^2}{m-1}} \quad (15)$$

where s_j is the standard deviation, m is the total number of factor observations or alternatives.

- iii. Calculate the Spearman correlation for every pair of factors with the equation:

$$\rho = 1 - \frac{6 \sum d_i^2}{m(m^2 - 1)} \quad (16)$$

where ρ = Spearman's rank correlation coefficient, d_i = difference between the two ranks of factors, m = number of factor observations.

Spearman's correlation (ρ) was employed to assess monotonic relationships between these factors, irrespective of whether there was a linear or non-linear relationship. The correlations analysis was determined for statistical significance at 5% ($p < .05$) and 1% ($p < .01$), the direction, whether positive or negative, and strength. For the strength, the threshold proposed by Pallant (2020) was employed: $0.09 \leq r \leq 0.29$ (weak), $0.30 \leq r \leq 0.49$ (medium) and ≥ 0.5 (strong).

- iv. Calculate the information content:

$$P_\xi = s_j \sum_{\xi'=1}^n \rho(g_\xi, g_{\xi'}) \quad (17)$$

where P_ξ is the information content of g_j

- v. Determine the weight estimates with the following equation:

$$w_j = \frac{P_\xi}{\sum_{\xi=1}^n P'_\xi} \quad (18)$$

where w_j is the objective weight of Y_ξ

5.6.6.2.5 Step 4: Determine the total composite score index for Manufacturing Operational Uncertainty Index (MOUI) and the overall level of operational uncertainty

The total composite score can be formulated as follows:

$$MOUI_j = \sum_{i=1}^n \xi_{sij}^{w_i} \quad (19)$$

where $MOUI_j$ is the composite score index of the combined constructs (ξ_{sij}), and w_j is the weighting of the construct – sum to a maximum of 1.

The score was used to determine decision-making and response levels of operational uncertainty. The four levels were explained earlier, as developed by Courtney (2001) on levels of uncertainty and Walker et al. (2003) on decision-making levels. Table 5.6 indicates level I to level IV.

Table 5.6: Levels of operational uncertainty

Level	Description	Score
I	Predictable outcomes	≤ 10
II	Alternative futures	10 – 40
III	Range of Future	41 – 79
IV	Highly uncertainty (true ambiguity	≥ 80

Source: Adapted from Courtney (2001) and Walker et al. (2003).

5.6.7 Management of operational uncertainty with Industry 4.0 and 5.0 technologies

Proposition three, that Industry 4.0 and 5.0 can manage the operational uncertainty in the manufacturing sector, was analysed with mean and standard deviation and a heatmap, frequency rank order on use and chi-square for association and proposition four with Pearson correlation analysis.

5.6.7.1 Heatmap techniques

Heatmap-based techniques improve the visualisation and interpretation of ibusiness data by offering intuitive and comprehensive representations of multidimensional information. These strategies facilitate the identification of patterns, trends, and anomalies that may

be challenging to detect with conventional data analysis techniques. Heatmaps utilise colour-coded matrices to elucidate linkages within data, rendering them an effective instrument for corporate information and decision-making. In the present research, it was used to highlight the impact of operational uncertainty on determinants of manufacturing operations. It was also used to highlight the capabilities of Industry 4.0 and 5.0 technologies in managing the responses to manufacturing operational uncertainty.

5.6.7.2 Frequency rank order on use

The frequency rank order method of ranking items is based on participants' frequency of selection of technology in use. This approach was employed to understand the technologies that were in use in the manufacturing firms.

$$f_i = n_i \quad (20)$$

where n is the number of items (technologies in use) i chosen by the firms. This frequency was calculated relative to the total sample and then ranked based on the table:

$$\{i, \%f_i, R_i\} \quad (21)$$

where R_i is the rank order. The high use was $> 70\%$, moderate use was $41 - 70$, and low use was up to 40% .

5.6.7.3 Chi-square of association

The Chi-Square (χ^2) test of association was used to assess whether there was a statistically significant association between the manufacturing sector industries and the technologies in use. The Chi-square test was calculated as follows:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \quad (22)$$

where O_i is the observed frequency of the item i , while E_i is the expected frequency, and these are calculated based on the assumption of independence. The strength of this association was determined with Cramer's V, (ϕ) with ≤ 0.1 (small), 0.3 (medium) and ≥ 0.50 large. A *post hoc* test was conducted as the Chi-square is an omnibus test, using the adjusted standardised residual:

$$r_{(adj)ij} = \frac{O_{ij} - E_{ij}}{\sqrt{E_{ij} \left(1 - \frac{m_i}{N}\right) \left(1 - \frac{n_j}{N}\right)}} \quad (23)$$

To determine the statistical significance, a Bonferroni correction was conducted to minimise the risk of Type I error, which can find statistical significance where it does not exist. The probability values for Bonferroni correction, Bf_p were converted using:

$$Bf_p = \frac{p}{n} \quad (24)$$

where p is the original statistical significance, and n is the number of tests, which were ten in the present analysis for industries - 2 (in use and not in use) and 5 for the industries. Statistical significance was achieved if the value was lower than the Bf_p value.

5.6.7.4 Correlation matrix analysis

A statistical correlation is a relationship between two variables that measures how they vary in relation to one another (Jagers & Loomis, 2020). It also offers information about how strongly the variables are related to one another and the direction of that relationship. The range of possible values for r is from -1 to +1. Regardless of the way in which the relationship is oriented, the strength of the relationship increases as the value of r becomes closer to 1 (Pallant, 2020). Perfect correlations are exceedingly uncommon, and when they do occur, researchers almost always attribute them to mathematical or methodological errors. Similarly, if one of the variables has a value of 0, it indicates that the other variable does not have a correlation with it. Before the correlation analysis, the empirical data were analysed for patterns and the existence of a relationship with scatter plots of operational uncertainty on firm performance. The correlation matrix of operational uncertainty on firm performance was analysed using both Pearson correlation and Spearman correlation. The Pearson product-moment correlation equation is as follows:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \quad (25)$$

where r is the correlation coefficient, X_i values of x variables in the sample, $\bar{X}$ is the mean of the values of x variables, Y_i values of y variables in the sample, $\bar{Y}$ is the mean of the values of y variables.

5.6.8 Integrated Fuzzy-DEMATEL, PLS-SEM and fsQCA approach

Proposition five, that the combinations of OPU2 (and its statistically significant dimensions from the PLS-SEM structural model), IRT, and OLN conditions lead to high or low sustained performance, and proposition six, on Integration of optimising methods, is necessary for optimum outcomes of QCA-based methods. The integrated Fuzzy-DEMATEL, PLS-SEM, and fsQCA approach was adopted in this research. Figure 5.3 highlights the 4-step integrative approach of Fuzzy-DEMATEL with PLS-SEM and fsQCA for configuration analysis for sustained performance.

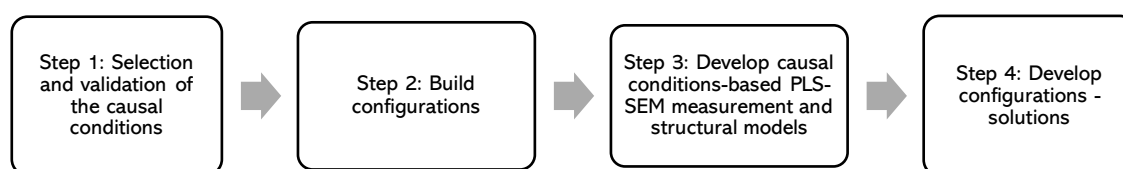


Figure 5.3: Steps to the integrative approach of Fuzzy-DEMATEL with PLS-SEM and fsQCA for configurations analysis for sustained performance.

Source: Author

5.6.8.1 Fuzzy-DEMATEL

In the present research, the causal conditions were empirically developed using a fuzzy decision-making trial and evaluation laboratory (DEMATEL). A fuzzy-DEMATEL is a multicriteria method for visualising the structure of complex causal-effect relationships (López-Ospina et al., 2022) and was employed in this research. It was originally developed at DEMATEL in Battelle Memorial Institute at the Geneva Research Center. This method focuses on exploring the relationship, a critical stage, rather than quantification as a base for developing a comprehensive outcome within a new focus area. Fuzzy-DEMATEL highlights the dominant relationships between factors and the interdependencies to effectively prioritise responses to operational uncertainty. Fuzzy-DEMATEL was conducted as a stepwise procedure based on expert group decision-making for optimum decision-making. The research adapted its approach from Lin and

Wu, (2008) and Yeh and Huang (2014) with measures of consistency for the DEMATEL Method from Shieh and Wu (2016) creating seven sub-steps.

5.6.8.1.1 Step 1: Decision goals, set of criteria, and decision-makers

The goal of the decision is to determine the relationship and interdependence of the factors. In multicriteria decision-making methods, there is no strict statistically-driven minimum sample size, although too many experts may result in repetitive information with little value from additional assessments. Tarei et al. (2021) support a smaller sample size, cautioning against a very large sample size as it can lead to a higher degree of inconsistency in decision-making. In the present research, the sample size was 22, which was within this range. Experts denote preferences and assign causalities using triangular fuzzy numbers (Jassbi et al., 2011) with the outcome averaged with the equation:

$$\tilde{z} = \frac{(\tilde{z}^1 \oplus \tilde{z}^2 \oplus \dots \oplus \tilde{z}^p)}{p} \quad (26)$$

where $\tilde{z}$ is the average of the assessment by the experts, p = is the number of the experts.

5.6.8.1.2 Step 2: Design the fuzzy linguistic scale

A three-point, five-point, or any customised scale can be developed. The five-point scale was selected for the operational uncertainty assessment based on the level of its influence on manufacturing operations. The degree of influence is expressed using five linguistic terms and triangular fuzzy numbers (Table 5.7 and Figure 5.4).

Table 5.7: Linguistic terms for fuzzy-DEMATEL model

Linguistic term		L	M	U
1	No influence (NI)	0	0.1	0.3
2	Very low influence (VI)	0.2	0.3	0.5
3	Low influence	0.3	0.5	0.7
4	High influence	0.5	0.7	0.9
5	Very high influence	0.7	0.9	1

Source: Author

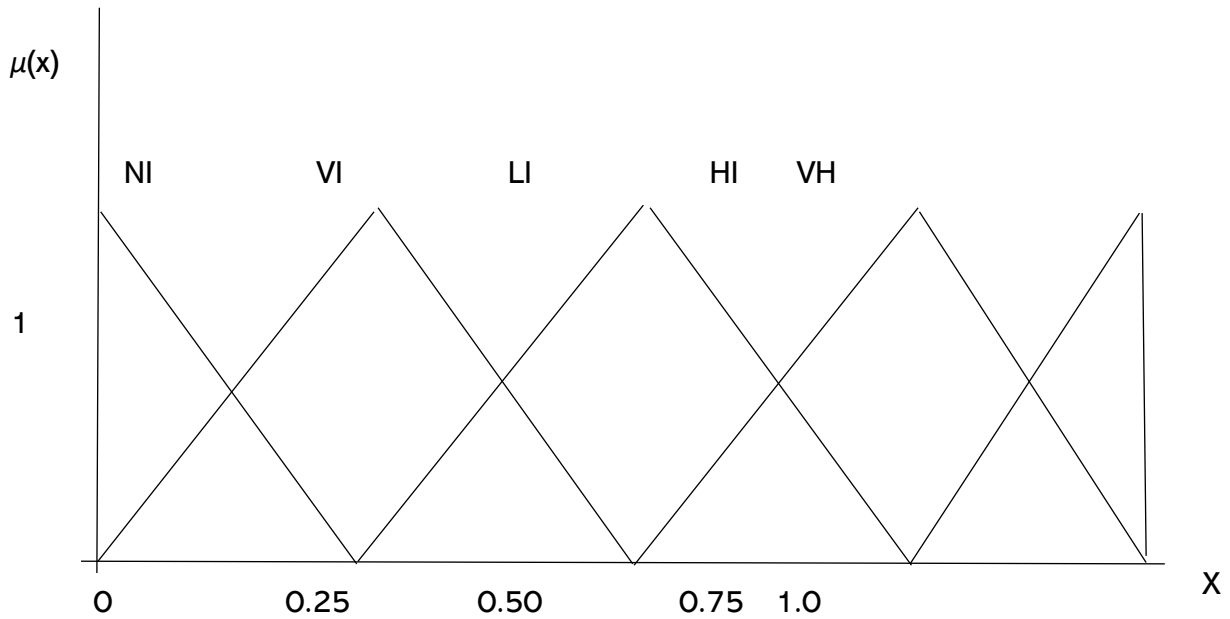


Figure 5.4: Linguistic terms and triangular fuzzy numbers

Source: Author

5.6.8.1.3 Step 3a: Generate a fuzzy matrix

Each expert, p , generates the matrix using the linguistic valuation with the linguistic terms using the level of influence and the linguistic fuzzy scale triangular numbers, lower-median-upper limits (l-m-u).

$$x_p(l, m, u) = \begin{bmatrix} 0 & x_{12}(l, m, u) & \dots & x_{1n}(l, m, u) \\ x_{21}(l, m, u) & 0 & \dots & x_{2n}(l, m, u) \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1}(l, m, u) & x_{n2}(l, m, u) & \dots & 0 \end{bmatrix} \quad (27)$$

5.6.8.1.4 Step 3b: Measure the agreement and consistency of decision-makers

Kendall's coefficient of concordance (W) was employed to assess the degree of agreement among the decision-makers (Teles, 2012). This method is a non-parametric approach for three or more distinct ranks. Kendall's W is analysed based on the following equation:

$$R_i = \sum_{j=1}^m r_{ij} \quad (28)$$

where i = individual rated criteria (dimension), m is the number of decision-makers where $m > 2$, in this study $m = 22$ rating n – dimensions, with:

$$R = m (n + 1) / 2$$

$$S = \sum_{i=1}^n (R_i - R)^2 \quad (29)$$

where S is a sum-of-squares statistics deviation over the row cumulates of ranks, R_i .

R is the mean for the R_i values. The Kendall's W concordance statistics (Marcinkiewicz, 2017), which range from 0 to 1, can be obtained from the equation:

$$W = \frac{12S}{m^2(n^3 - n)} \quad (30)$$

In addition, an analysis was conducted with acceptable levels of agreement to evaluate individual-level consistency using the corrected item-total correlation. The item-total correlation refers to the degree of linear association between an individual item and the overall scale total. The greater the correlation among experts, the higher the inter-item correlations. The drawback of the item-total correlation method is its redundancy. To address overlap, the item to be correlated is excluded from the scale total. It refers to the relationship between a specific item and the overall score excluding that item. In the present study, 22 experts were evaluated to yield 22 expert-total correlations. The correlation of each expert with the aggregate of the other 21 experts. The corrected-item total correlation is denoted as follows:

$$\text{Corrected – item total correlation } (X_i) = \text{corr} \left(X_i, \sum_{j=1}^{22} X_j - X_i \right) \quad (31)$$

where $X_1, X_2, \dots, X_{22}$ are the experts and corr being the Pearson correlation and $1 \leq i, j \leq 22$. The Intraclass Correlation Coefficient (ICC) values indicate the level of agreement or reliability among the experts' ratings for each construct (Shrout & Fleiss, 1979). Based on the ICC interpretation of > 0.90 : Excellent agreement, $0.75 - 0.90$: Good agreement, $0.50 - 0.75$: Moderate agreement and < 0.50 : Poor agreement.

5.6.8.1.5 Step 3c: Generate the mean fuzzy direct-relation matrix

The arithmetic mean was then developed from the experts' assessment to generate the direct relation matrix. This was based on all 22 experts, as they were all retained after Kendall's coefficient of concordance (W), Corrected item-total correlation, and intraclass correlation. The intraclass correlation analysis was based on a two-way correlation coefficient focusing on absolute agreement (closeness of the expert measures to each other). The direct relation matrix generated is the same as the expert's pairwise comparison matrix.

5.6.8.1.6 Step 4: Normalise the fuzzy direct relation matrix

Conversion from a linear to a normalised scale was conducted to obtain a compatible scale (Yeh & Huang, 2014). The normalised fuzzy direct-relation matrix can then be determined with the following equation:

$$\tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{r} = \left(\frac{l_{ij}}{r}, \frac{m_{ij}}{r}, \frac{u_{ij}}{r} \right) \quad (32)$$

where

$$r = \max_{i,j} \left\{ \max_i \sum_{j=1}^n U_{ij}, \max_j \sum_{i=1}^n U_{ij} \right\} \quad i, j \in \{1, 2, 3, \dots, n\} \quad (33)$$

5.6.8.1.7 Step 5: Determine fuzzy total-relation matrix

The fuzzy total-relation matrix can be determined with the following equation:

$$\tilde{T} = \lim_{k \rightarrow +\infty} (\tilde{X}^1 \oplus \tilde{X}^2 \oplus \dots \oplus \tilde{X}^k) \quad (34)$$

where $\tilde{T}$ is the fuzzy total relation-matrix from the normalised direct relation-matrix, $\tilde{X}$.

$$\tilde{T} = \begin{bmatrix} \widetilde{t_{11}} & \widetilde{t_{12}} & \dots & \widetilde{t_{1n}} \\ \widetilde{t_{21}} & \widetilde{t_{22}} & \dots & \widetilde{t_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{t_{m1}} & \widetilde{t_{m2}} & \dots & \widetilde{t_{mn}} \end{bmatrix} \quad (35)$$

and the element of the fuzzy total-relation matrix is expressed as:

$\tilde{t}_{ij} = (l_{ij}^{\prime\prime}, m_{ij}^{\prime\prime}, u_{ij}^{\prime\prime})$, and calculated with equations as follows:

$$\begin{aligned} [l_{ij}^{\prime\prime}] &= x_l \times (I - x_l)^{-1} \\ [m_{ij}^{\prime\prime}] &= x_m \times (I - x_m)^{-1} \\ [u_{ij}^{\prime\prime}] &= x_u \times (I - x_u)^{-1} \end{aligned} \quad (36)$$

5.6.8.1.8 Step 6: Defuzzify matrices of total relationships

$$DF_{ij} = \frac{((u_{ij} - l_{ij}) + (m_{ij} - l_{ij}))}{3} + l_{ij} \quad (37)$$

5.6.8.1.9 Step 7: Causal analysis

Causal relation analysis is used to determine the most important factor and how it is classified to understand the cause and effect. This is determined with the following equations:

$$D_i = \sum_{j=1}^n w_{ij} \quad (38)$$

$$R_j = \sum_{i=1}^n w_{ij} \quad (39)$$

$$D + R \quad (40)$$

$$D - R \quad (41)$$

where D_i is the sum of rows while R_j is the sum of the columns. $D + R$ represents the degree of importance of the factor, and D-R represents the net effects that the factor contributes to the system. A graph is developed to depict a cause-effect diagram.

5.6.8.2 PSL-SEM structural model

Having done the measurement model for validity and reliability, the study also analysed the structural model to understand the level of the relationship between the conditions and outcomes.

In addition, the LOCs were analysed for variance inflation factor (VIF) checks for the structural model specification, which was used to validate the central assumption of multicollinearity. The reason for this was that in the presence of multicollinearity, a linear relationship between two explanatory variables might lead to unwarranted increases in the standard errors of the coefficients (Salmerón et al., 2018). A multicollinearity equation can be written as:

$$VIF = \frac{1}{1 - R_j^2} \quad (42)$$

where R_j^2 is the proportion of the variance from the regressions of the explanatory variables, $j = 1, 2, \dots, p$.

The quality assessment of the model confirms the validity and accuracy of the results produced by the structural model of the study. This was followed by assessing the model's explanatory power, R^2 , effect size, f^2 and predictive relevance, Stone-Geisser's Q^2 (Hair et al., 2019). The f^2 measures a specific causal condition on an outcome condition by examining the change in R^2 when a dimension is included versus when it is excluded from the model. The f^2 is formulated as follows (Cohen, 1988):

$$f^2 = \frac{R_{il}^2 - R_{el}^2}{1 - R_{il}^2} \quad (43)$$

where R_{il}^2 is the R^2 value of the outcome condition when a specific operational uncertainty dimension is included, while R_{el}^2 is the R^2 value of the outcome condition when a specific operational uncertainty dimension is included in the model.

The R^2 in its explanatory power assesses the proportion of variance in an outcome condition explained by its causal conditions, analysed with the equation:

$$R^2 = 1 - \frac{SS_{rd}}{SS_{to}} \quad (44)$$

where SS_{rd} is the sum of the squares of the residuals that are unexplained variance in the causal outcome, while SS_{to} is the total sum of squares of the total variance in outcome variance given as an observed value around the mean. Hair et al. (2019) indicated that a $Q^2 > 0$ indicates good predictive relevance.

The predictive relevance of the endogenous variables is calculated using the following equation:

$$Q^2 = 1 - \frac{SSE}{SSO} \quad (46)$$

where SSE is the sum of the squared prediction errors, and SSO is the sum of the squared prediction errors. The structural model was then computed to determine the path of the dimensions on outcome conditions, sustained performance, and HOC and operational uncertainty on sustained performance. This was determined by the path coefficient, β with statistical significance, $p < .005$, and t-statistics, which should be higher than ± 1.96 .

5.6.8.3 Confirm segments of empirical data

This step confirms segments of empirical data and helps to validate the accuracy of the model, as well as the robustness and sensitivity test, as it was conducted with finite mixture (FIMIX) segmentation (Sarstedt et al., 2011). The optimum number of segments (OS) was calculated with the following equations:

$$OS = \frac{TO}{NE * 10} \quad (47)$$

where TO is the total number of observations, which was 262 in this research, with NE being the number of variables linked to the outcomes, which is 5, so $OS = 3.28$, equating to three segments. All segments had sizes that were more than the recommended minimum size of 5%. The AIC3 (modified AIC with Factor 3), CAIC (consistent AIC) and EN (normed entropy statistic) were used as the fit indices.

Segments need to have a normed entropy statistic above 0.5, indicating that all these segments are acceptable for further assessment. The segment with a minimum AIC3 and CAIC confirms the optimal segment. If there are contradictory segments with minimum AIC3 or CAIC, then a summed fit was done, and the overall minimum segment was selected as the optimum segment. If the optimum segment is 1, then these results confirm that there were no hidden heterogeneity issues, and as such, the data analysed as a whole were acceptable.

5.6.8.4 Develop FSQCA – solutions

The configurations approach reveals coherent patterns of organisation by identifying interpretive schemas and the "how" they connect to characteristics and structural processes (Harlacher & Reihlen, 2014; Damke et al., 2018). The FsQCA is based on cases that can be interpreted in various ways, such as theoretical entities or empirical units; QCA specifically conceptualises cases as sets of attribute configurations (Misangyi et al., 2017; Greckhamer et al., 2018). As a result, the configurations approach reveals coherent patterns of organisation by identifying interpretive schemas and the "how" they connect to characteristics and structural processes (Damke et al., 2018).

The configurations illustrate an arrangement of elements facilitated by interdependent systems established through central organising themes. The use of configurations also possesses a prognostic capacity, as, within this framework, an organisation can employ diverse perspectives on knowledge to ascertain its present state and identify potential future positions to pursue. There may be a complementarity of these characteristics within configurations, with each attribute either reinforcing the effects of the other or compensating for the deficiencies of the other. Hence, not all attributes need to be present in each configuration (equifinality) (Fiss, 2011).

Configuration leads to specific outcomes if there are sufficient conditions or combinations. Analysis of the different cases can help to identify the sufficient conditions to achieve the objective, which is sustainable performance during operational uncertainty. When these conditions occur constantly, they are termed sufficient conditions within the different cases, and these are necessary conditions. A critical requirement before identifying the conditions using fsQCA is to identify and assign the set of members of observations (Ragin, 2008b; Rasoolimanesh et al., 2021). This assigning is commonly known as calibration, and it can use different methods based on the data type. The

calibration is from 0 for full-non membership to 1 for full membership. Schneider and Wagemann (2012) recommended a partial value, also known as “difference-in-degree”, which is based on Likert scale-based fuzzy value set (ordinal) or continuous fuzzy, which will provide more accurate analysis than a dichotomous value of 0 and 1, which is more useful for qualitative analysis. The calibration allows the analysis of the data and identifies the high and low levels of predictor and outcome to identify the sufficient and necessary conditions.

Rasoolimanesh et al. (2021) highlighted that the “truth table” works on the logic of sufficiency to postulate that when a certain condition is present, that expected outcome also exists. Simply put, if the configuration produces the expected outcome, the combination of the predictors is sufficient. In the truth table, all combinations of conditions are identified. For different conditions, there can be sufficient and necessary conditions; others can be sufficient but not necessary, while others are necessary but not sufficient, and still others are neither sufficient nor necessary. As fsQCA is based on Boolean algebra, the Boolean minimisation methods can be used to capture patterns of multiple-conjunctural causality and to simplify complex data structures rationally and comprehensively. Three Boolean operations are used, these being the negation operations ($\sim$), logical AND ($*$) and logical OR ($+$) (Rasoolimanesh et al., 2021).

The cut-off frequency for conditions (raw coverage) was greater than or equal to 3 for the analysis. This helps ensure that very few conditions regarded as not meaningful are filtered out. The consistency and coverage of the configurations assist in identifying the sufficiency and necessity of the configuration for the specific outcome (Ragin, 2008b). Consistency highlights the proportion of the cases that are present in a combination for the specific outcome with the consistency calculated (Ragin, 2009):

$$Consistency (Con_j) = \frac{\sum(\min Con_j, Y_i)}{\sum(Con_j)} \quad (49)$$

where Con_j is the fuzzy-set membership score of the configuration for each case, j . Y_j is the membership outcome of the case, j while $\min$ represents the lowest membership of Con_j and Y_j . A consistency score of 0.8 confirms the sufficiency of the configuration.

Coverage indicates how well the configurations explain the outcome of interest (Rasoolimanesh et al., 2021; Salmerón et al., 2018) and is determined using the following formula:

$$Coverage (Con_j) = \frac{\sum(\min Con_j, Y_i)}{\sum(Y_j)} \quad (50)$$

A coverage score of 0.2 confirms the sufficiency of the configuration with the fuzzy set membership scores higher than 0.5 obtained from the configurations (Ragin, 2009; Rasoolimanesh et al., 2021).

5.7 Research quality, rigour and robustness

Multiple validities can only be attained if the design as a whole is of high quality. Validity, in this context, refers to whether a given research method satisfies the necessary combination or set of quantitative method validities. Table 5.8 specifies the quality controls linked to the different relevant analytical methods. Within this analysis, quality controls are convergence, composite, reliability, and discriminant validity.

Table 5.8: Analytical methods with quality controls

Analytical method	Quality controls
Measurement model (Lower-order and higher-order construct analysis)	Composite reliability and reliability Convergence validity, discriminant validity
Structural model	VIF, f^2 , R^2 , Stone-Geisser's Q^2 FIMIX
Fuzzy-DEMATEL	Kendall's coefficient of concordance (W) Corrected item-total correlation Intraclass Correlation Coefficient (ICC)
Relative Importance Index	Cronbach Alpha
Composite score analysis	Cronbach alpha Weighted estimates Spearman's rank correlation coefficient
FsQCA	Consistency and coverage Necessary conditions

Source: Author

The expert assessment data, which were analysed using Fuzzy-DEMATEL, used Kendall's coefficient of concordance (W), corrected item-total correlation and intraclass correlation coefficient (ICC) to measure agreement and consistency. The PLS-SEM measurement model

was analysed using reliability and validity measures, while the structural models used VIF and predictive relevance (Stone-Geisser's Q^2). The FIMIX analysed the underlying segments. Analysis was also conducted with FsQCA with quality control for rigour and robustness with necessary and sufficient conditions, consistency and coverage.

5.8 Methodological limitations

Research studies have their own set of possible flaws that are often outside the research's control. Instead, they are tied inextricably to aspects of the study's methodology, data collection methods, statistical models, and/or financial resources. In the present study, several methodological limitations were present, including sampling bias and generalisability issues from using non-probability sampling methods, although these were minimised with probability multistage sampling. There is also a debate on the strengths and limitations of fsQCA; thus, it was important to minimise any potential methodological bias with rigor and robustness in the analysis, as the findings of the fsQCA are regarded as "moderately generalisable." Hence, in addition, multi-quantitative methods strengthened the research. With regard to administrative weaknesses, there was resource intensity with a study across the manufacturing industries, which was mitigated by a hybrid data-gathering approach. The three main methods employed in this study were the Fuzzy-DEMATEL, PLS-SEM and fcQCA. Despite their strength and robustness, they have certain limitations which should help contextualised the results.

The fuzzy DEMATEL method relies heavily on expert judgments, which can introduce subjectivity and bias into the decision-making process. Aggregating these judgments is crucial, as improper aggregation can lead to inaccurate results (Fakhrzad et al., 2021). The method's effectiveness depends on the quality and diversity of expert input, which can vary significantly based on the context and the experts involved (Abikova, 2020). In this study, this issue was mitigated by introducing Kendall's coefficient of concordance (W), the correct correlation, and the Intraclass Correlation Coefficient (ICC) to ensure acceptable levels of agreement and consistency among the experts. Table 5.8 of analytical methods with quality controls is central to maximizing the use of analytical methods while minimising their challenges. Gligor and Bozkurt (2020) posited that the symmetric approach such as PLS-SEM fails to account for the complexities due to its tendency to generalise relationships. This traditional statistical method quantify the overall impact of individual variables while keeping other factors unchanged, known as the "net effect"

(Witt & Jackson, 2016). On the other hand, asymmetric modelling, exemplified by QCA, is posited as a viable stand-alone method due to its adequate explanatory power regarding the relationships of interest (Gligor & Bozkurt, 2020) and as it focuses on the causal effects arising from combinations of conditions rather than assessing the net effect of individual variables. Conversely, QCA exhibits several limitations. Fainshmidt et al. (2020) identified various limitations of QCA, notably the challenges in interpreting results, particularly with numerous causal conditions, and the sensitivity inherent in the data calibration process, among other issues.

5.9 Chapter Conclusion

This methodology chapter discusses the rationale behind selecting methods and offers guidelines for setting up, organising, planning, designing, and carrying out the research. It describes the theoretical concepts that inform the choice of methods to be applied, situates the choice of methods within the larger context of academic work, and assesses its relevance to the investigation of the research problem.

Chapter 6

Operational Uncertainty in Manufacturing

6.1 Introduction

The first objective of the study was to develop a comprehensive understanding of operational uncertainty in manufacturing. This was done by analysing the empirical data obtained from the survey involving the business experts and individuals from the business firms. Expert scientific judgment entails making considered judgments and decisions rooted in extensive knowledge and skills. The scientific conclusion was achieved by combining expert judgments from content specialists and statisticians, focusing on rigour and objectivity. The empirical data from the firm survey starts with descriptive statistics about the operational uncertainty indicators and the instrument's internal consistency reliability.

In line with the expanded 3-step process, this chapter confirms the constructs (Lambert & Newman, 2023). It starts with a scatter plot, followed by corrected item-total correlation and the measurement model from the structural equation modelling partial least square (PLS-SEM) for the dimension (Lower-order constructs) to assess operational uncertainty as a multi-dimensional construct (proposition 1). The second part of the chapter analysis describes assessing operational uncertainty as a norm in the manufacturing sector with the relative importance index and the level of operational uncertainty with the operational uncertainty index – composite score (proposition 2). The last part of this comprehensive understanding of operational uncertainty in manufacturing is the analysis of operational uncertainty dimensions on operations determinants.

6.2 Descriptive statistics and reliability

The participants were requested to indicate their level of agreement with the statement based on a 5-point Likert scale, with 1 representing a participant 'strongly disagree', increasing to 5 representing 'strongly agree' with the statement. This included 36 statements (VAR1 – VAR36), with the full indicator description of VAR shown in Appendix

C. Table 6.1 indicates the analysis of the descriptive statistics from the firm survey data and provides insights into the central tendency and the spread of the empirical data.

The overall mean range for the statements was $M = 3.32 - 4.26$, with ten out of the 36 statements showing a mean higher than 4.00, indicating that the participant responses were in the range of 'agree' to 'strongly agree'. The median ranged from $Mdn = 3.00$ to 4.00. The 5% trimmed mean for the variables was generally close to the original mean even after removing the most extreme 5% of responses, which suggests stability in the central tendency in this empirical data.

The statement with which the participants most highly agreed was VAR1 – 'growing geopolitical tension has resulted in problems in our firm's manufacturing operations resulting in rising input (raw or semi-processed material) prices'. The response showed a mean, $M = 4.26$ ($SD = 0.795$) with a 95% confidence interval of $[4.17, 4.36]$ and a median, $Mdn = 4.00$. The 5% trimmed mean was 4.35%, indicating that the mean remains high and close to the original mean even after removing the most extreme 5% of responses. This was followed by VAR4 ($M = 4.25$, $SD = 0.735$; 95% CI: $[4.16, 4.34]$), which represents the statement that growing geopolitical tension has resulted in problems in our firm's manufacturing operations resulting in increased costs of importing involving customs, tariffs, and other import duties.

The statements with which the participants least agreed showed a mean (M) < 3.50 . The lowest variable was VAR29 for the statement, 'The entrenchment power of large firms is impacting our firm operations; as such, the dominant firms engage in unfair business practices to the detriment of our firm' ($M = 3.32$, $SD = 1.077$; 95% CI: $[3.19 - 3.45]$). The 5% trimmed mean for the variable was 3.33, and the median, $Mdn = 3.00$. This was followed by VAR32 for the statement, 'The entrenchment power of large firms is impacting our firm operations as such product marketing in the firm suffers due to a lack of financial advantage or resources for marketing and sales' ($M = 3.35$, $SD = 1.144$; 95% CI: $[3.21 - 3.49]$). The third lowest was VAR28, which represented the statement 'Skills for future work are impacting our manufacturing operation, as such virtual collaboration is now the norm in the firm' ($M = 3.43$, $SD = 1.165$; 95% CI: $[3.29 - 3.57]$).

Table 6.1: Descriptive statistics from the business firm survey data

Indicator	Mean (M)	95% Confidence Interval for Mean		5% Trimmed Mean	Median (Mdn)	Std. Deviation (SD)	Skewness	Kurtosis
		Lower Bound	Upper Bound					
VAR1	4,26	4,17	4,36	4,35	4,00	0,795	-1,523	3,667
VAR2	3,72	3,63	3,81	3,76	4,00	0,730	-1,352	2,898
VAR3	4,06	3,97	4,16	4,12	4,00	0,788	-0,874	1,322
VAR4	4,25	4,16	4,34	4,32	4,00	0,735	-1,362	3,785
VAR5	3,54	3,43	3,65	3,55	3,00	0,891	0,163	-0,613
VAR6	3,83	3,73	3,93	3,86	4,00	0,824	-0,251	-0,516
VAR7	3,71	3,60	3,82	3,75	4,00	0,913	-0,345	-0,233
VAR8	3,52	3,41	3,64	3,54	4,00	0,929	-0,154	-0,455
VAR9	4,06	3,95	4,18	4,14	4,00	0,949	-0,773	0,024
VAR10	3,86	3,74	3,97	3,91	4,00	0,950	-0,334	-0,658
VAR11	3,93	3,82	4,05	3,99	4,00	0,944	-0,550	-0,361
VAR12	3,94	3,82	4,06	4,00	4,00	0,969	-0,539	-0,501
VAR13	4,14	4,03	4,25	4,22	4,00	0,879	-0,825	0,119
VAR14	4,02	3,91	4,13	4,09	4,00	0,918	-0,705	-0,028
VAR15	3,84	3,71	3,96	3,89	4,00	1,047	-0,495	-0,624
VAR16	3,80	3,68	3,92	3,84	4,00	0,987	-0,283	-0,899
VAR17	4,01	3,90	4,11	4,08	4,00	0,844	-0,900	1,121
VAR18	3,97	3,87	4,08	4,03	4,00	0,877	-0,566	-0,190
VAR19	3,77	3,65	3,90	3,83	4,00	1,039	-0,488	-0,420
VAR20	3,69	3,56	3,82	3,73	4,00	1,061	-0,383	-0,694
VAR21	3,57	3,45	3,70	3,59	3,00	1,025	0,007	-0,888
VAR22	3,88	3,76	3,99	3,92	4,00	0,959	-0,383	-0,757
VAR23	4,14	4,03	4,24	4,21	4,00	0,873	-0,897	0,540
VAR24	4,23	4,13	4,32	4,28	4,00	0,779	-0,866	0,702
VAR25	3,51	3,38	3,64	3,53	3,00	1,085	-0,047	-0,940
VAR26	3,51	3,38	3,64	3,53	3,00	1,085	-0,047	-0,872
VAR27	3,65	3,52	3,77	3,67	4,00	1,050	-0,089	-1,060
VAR28	3,43	3,29	3,57	3,47	3,00	1,165	-0,089	-0,938
VAR29	3,32	3,19	3,45	3,33	3,00	1,077	0,139	-0,647
VAR30	3,85	3,72	3,97	3,90	4,00	1,036	-0,399	-0,797
VAR31	3,50	3,36	3,64	3,54	3,00	1,174	-0,179	-0,986
VAR32	3,35	3,21	3,49	3,38	3,00	1,144	0,038	-0,920
VAR33	4,01	3,89	4,13	4,07	4,00	0,977	-0,570	-0,695
VAR34	3,56	3,43	3,69	3,58	3,00	1,055	-0,142	-0,804
VAR35	3,44	3,30	3,57	3,45	3,00	1,098	0,088	-0,978
VAR36	3,59	3,46	3,72	3,61	3,00	1,078	-0,007	-1,007

Reliability (VAR1 – VA36) – $\alpha = 898$

Source: Author

The variable lower than $M = 3.50$ was VAR35 for the statement that the firm does not leverage process capabilities to improve the design or processing of products ($M = 3.44$, $SD = 1.098$; 95% CI: [3.30 – 3.57]).

Skewness and kurtosis are critical in assessing the normality assumptions in statistical analysis, as they provide insights into the shape and tails of a distribution (Hatem et al., 2022). The skewness ranged from -1.523 to 0.163, while kurtosis ranged from -1.060 to 3.785, which is within the normal or near-normal distribution range based on the guidelines of Hair et al. (2010). The instrument reliability with Cronbach Alpha coefficient (α) of VAR1-VAR36 was $\alpha = 0.898$, indicating excellent internal consistency. This reflects how well these indicators measure the construct of operational uncertainty and excellent reliability based on Pallant's guidelines (Pallan, 2020).

6.3 Corrected Item-Total Correlation and Measurement model

The first research proposition focused on whether operational uncertainty is a multi-dimensional construct in manufacturing and can be recapped as follows:

Proposition 1: Operational uncertainty is a multi-dimensional construct

This was investigated with the scatter plot, corrected item-total correlation, and the measurement model of the PLS-SEM, fuzzy-DEMATEL, and higher-order construct measurement model and higher-order for operational uncertainty.

6.3.1 Scatter plot

The scatter plot of the dimensions is presented in Figure 6.1 and is particularly useful for identifying correlation patterns in a dataset. This was done by a visual representation of the relationship between two variables, allowing for quick identification of trends. In these data, there is evidence of positive correlations between the different dimensions of operational uncertainty. Based on the upward trends, the scatter points follow a diagonal line moving from the bottom left to the top right of a cell. This indicates that these pairs of dimensions are likely to have a positive correlation, with most of the pairs showing this correlation pattern. This is evident in pairs such as GPT and ESS, amongst others. Some, like PRU and ESS, as well as PCV and GWB, show very little correlation pattern. These correlation patterns need statistical confirmation.

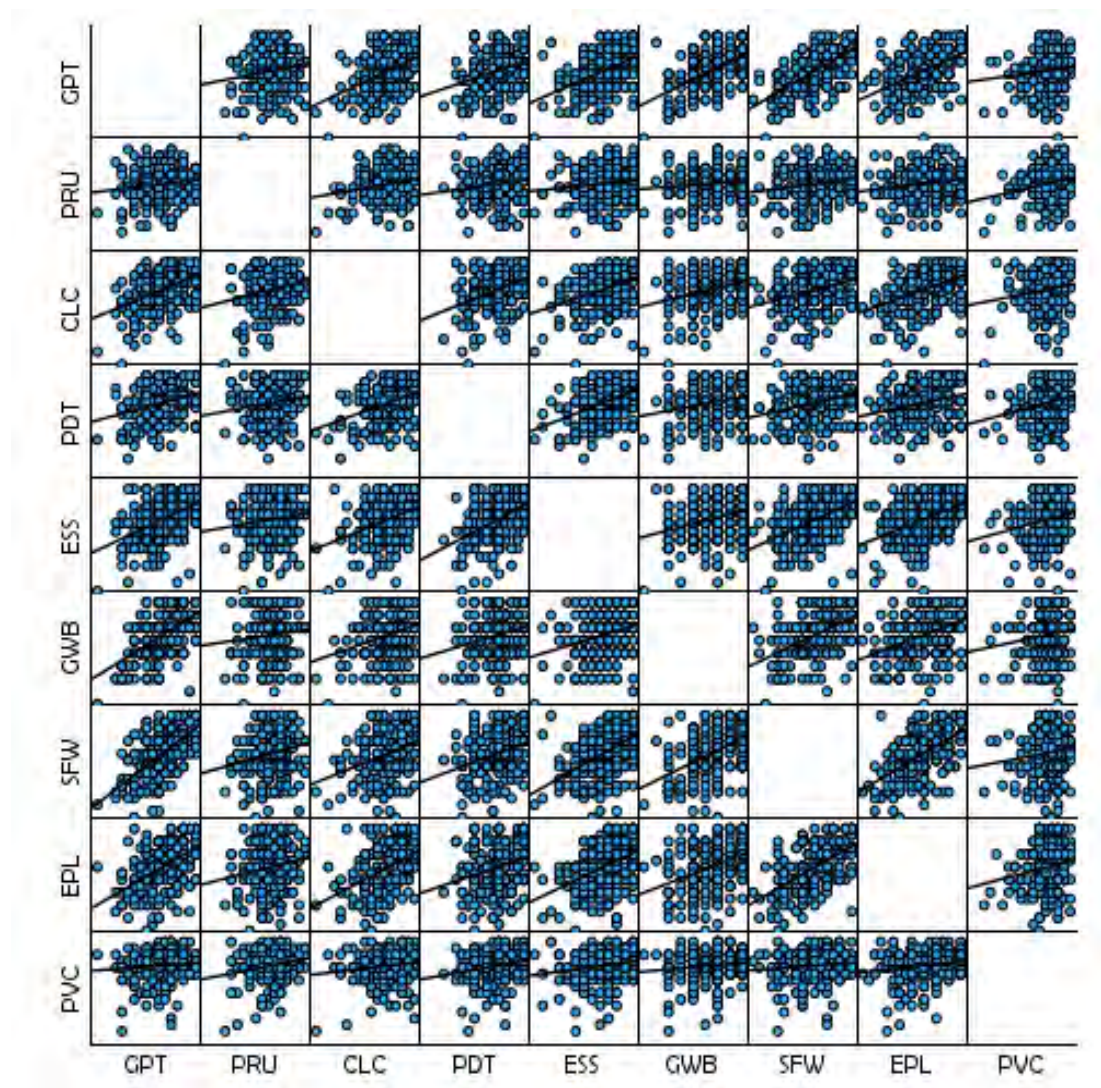


Figure 6.1: Scatter plot matrix of the operational uncertainty dimensions

Source: Author

6.3.2 Corrected Item-Total Correlation

Table 6.2 provides the corrected item-total correlation Pallant (2020) proposed a threshold of 0.3 for acceptable values to indicate that the item is reasonably consistent with the rest of the scale. In these data, 29 of 36 items had a value of 0.303 – 0.600.

Table 6.2: Corrected Item-Total Correlation

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR1	132,18	262,219	,167	,898
VAR2	132,73	259,486	,303	,897
VAR3	132,38	259,409	,280	,897
VAR4	132,20	262,382	,177	,898
VAR5	132,91	260,045	,219	,898
VAR6	132,62	263,256	,120	,899
VAR7	132,73	261,070	,177	,899
VAR8	132,92	257,174	,305	,897
VAR9	132,39	253,502	,421	,895
VAR10	132,59	253,952	,405	,895
VAR11	132,52	252,756	,449	,895
VAR12	132,51	251,822	,468	,894
VAR13	132,31	256,450	,352	,896
VAR14	132,42	255,686	,361	,896
VAR15	132,61	251,848	,427	,895
VAR16	132,65	255,769	,329	,896
VAR17	132,44	256,814	,355	,896
VAR18	132,47	252,702	,490	,894
VAR19	132,67	252,643	,406	,895
VAR20	132,76	246,484	,586	,892
VAR21	132,87	250,624	,477	,894
VAR22	132,57	251,848	,472	,894
VAR23	132,31	259,693	,237	,898
VAR24	132,22	258,140	,335	,896
VAR25	132,94	245,958	,587	,892
VAR26	132,94	245,544	,600	,892
VAR27	132,80	248,382	,533	,893
VAR28	133,02	244,567	,582	,892
VAR29	133,13	249,002	,499	,894
VAR30	132,60	250,731	,468	,894
VAR31	132,95	243,775	,600	,892
VAR32	133,10	245,872	,556	,892
VAR33	132,44	252,913	,427	,895
VAR34	132,89	247,846	,547	,893
VAR35	133,01	246,172	,574	,892
VAR36	132,86	250,129	,465	,894

Source: Author

These items were from all nine dimensions of operational uncertainty. The seven items with a low value included VAR1, VAR3-VAR7 and VAR23. Significantly, these indicators

are related to geopolitical tension and policy uncertainty. These items might have been problematic because they did not contribute to the scale. However, they were initially retained as they would not significantly impact Cronbach's Alpha if the item was deleted. The final decision was made to retain or remove them after further assessment, which was done using the full measurement model of the PLS-SEM.

6.3.3 Measurement model – PLS-SEM dimensions

6.3.3.1 Specification of the measurement model

The measurement model first determined whether its latent constructs are best specified as reflective or formative. Formative models are used when indicators cause the construct, while reflective models are used when indicators are effects of the construct.

Table 6.3 presents the CTA for the constructs involving variables, with the purpose of determining whether a set of items for each of the nine dimensions should be modelled as reflective or formative in the PLS-SEM. The table of results indicates the grouping of variables being analysed for the dimension showing the initial and rearranged grouping items. The estimated value of the tetrad from the original sample was generally low, ranging from $M = -0,093$ to $0,169$, with very low bias, which is the difference between the sample mean and the original sample estimate, suggesting stable estimates. The majority, about 80%, were not statistically significant, indicating that this was a reflective model. This was confirmed by the CI Low and CI Up, which represent the lower and upper bounds of the 95% confidence interval for the tetrad estimate. Since zero falls within this interval, the tetrad is not significantly different from zero.

Table 6.3: Confirmatory tetrad analysis of the model

Dimensions		Mean sample	T statistics	P values	Bias	CI low	CI up	Alpha adj.	z(1-alpha)	CI low adj.	CI up adj.
PCV	1: VAR1,VAR2,VAR3,VAR4	-0,012	0,873	0,383	0,000	-0,035	0,011	0,050	1,960	-0,040	0,015
	2: VAR1,VAR2,VAR4,VAR3	-0,019	1,236	0,217	0,000	-0,045	0,006	0,050	1,960	-0,050	0,011
PRU	1: VAR5,VAR6,VAR7,VAR8	0,028	1,718	0,086	0,000	0,002	0,056	0,050	1,960	-0,004	0,061
	2: VAR5,VAR6,VAR8,VAR7	0,006	0,328	0,743	0,000	-0,024	0,037	0,050	1,960	-0,030	0,043
CLC	1: VAR10,VAR11,VAR12,VAR9	-0,020	0,829	0,407	0,000	-0,058	0,020	0,050	1,960	-0,066	0,027
	2: VAR10,VAR11,VAR9,VAR12	-0,014	0,601	0,548	0,000	-0,052	0,024	0,050	1,960	-0,059	0,031
PTB	1: VAR13,VAR14,VAR15,VAR16	0,021	0,601	0,548	0,000	-0,036	0,076	0,050	1,960	-0,046	0,086
	2: VAR13,VAR14,VAR16,VAR15	0,064	1,977	0,048	0,000	0,011	0,119	0,050	1,960	0,001	0,129
ESS	1: VAR17,VAR18,VAR19,VAR20	0,041	1,556	0,120	0,000	-0,002	0,085	0,050	1,960	-0,010	0,093
	2: VAR17,VAR18,VAR20,VAR19	0,017	0,474	0,635	0,000	-0,041	0,072	0,050	1,960	-0,051	0,083
GWB	1: VAR21,VAR22,VAR23,VAR24	0,107	3,621	0,000	-0,001	0,061	0,159	0,050	1,960	0,051	0,169
	2: VAR21,VAR22,VAR24,VAR23	0,108	3,670	0,000	-0,002	0,062	0,160	0,050	1,960	0,052	0,169
SFW	1: VAR25,VAR26,VAR27,VAR28	-0,093	1,605	0,109	0,001	-0,193	0,001	0,050	1,960	-0,212	0,020
	2: VAR25,VAR26,VAR28,VAR27	-0,026	0,551	0,581	0,001	-0,106	0,052	0,050	1,960	-0,121	0,067
EPL	1: VAR29,VAR30,VAR31,VAR32	0,169	3,234	0,001	-0,002	0,086	0,259	0,050	1,960	0,069	0,276
	2: VAR29,VAR30,VAR32,VAR31	0,106	1,887	0,059	-0,001	0,015	0,201	0,050	1,960	-0,003	0,219
GPT	1: VAR33,VAR34,VAR35,VAR36	0,041	1,098	0,272	0,000	-0,021	0,103	0,050	1,960	-0,032	0,115
	2: VAR33,VAR34,VAR36,VAR35	0,068	1,960	0,050	0,000	0,011	0,127	0,050	1,960	0,000	0,138

Source: Author

6.3.3.2 Factor loadings and model fit

Table 6.4 presents the model's factor loadings. The factor loading is important in PLS-SEM to ensure model validity by achieving a good model fit and so enhancing the model's predictive power (Hair & Alamer, 2022).

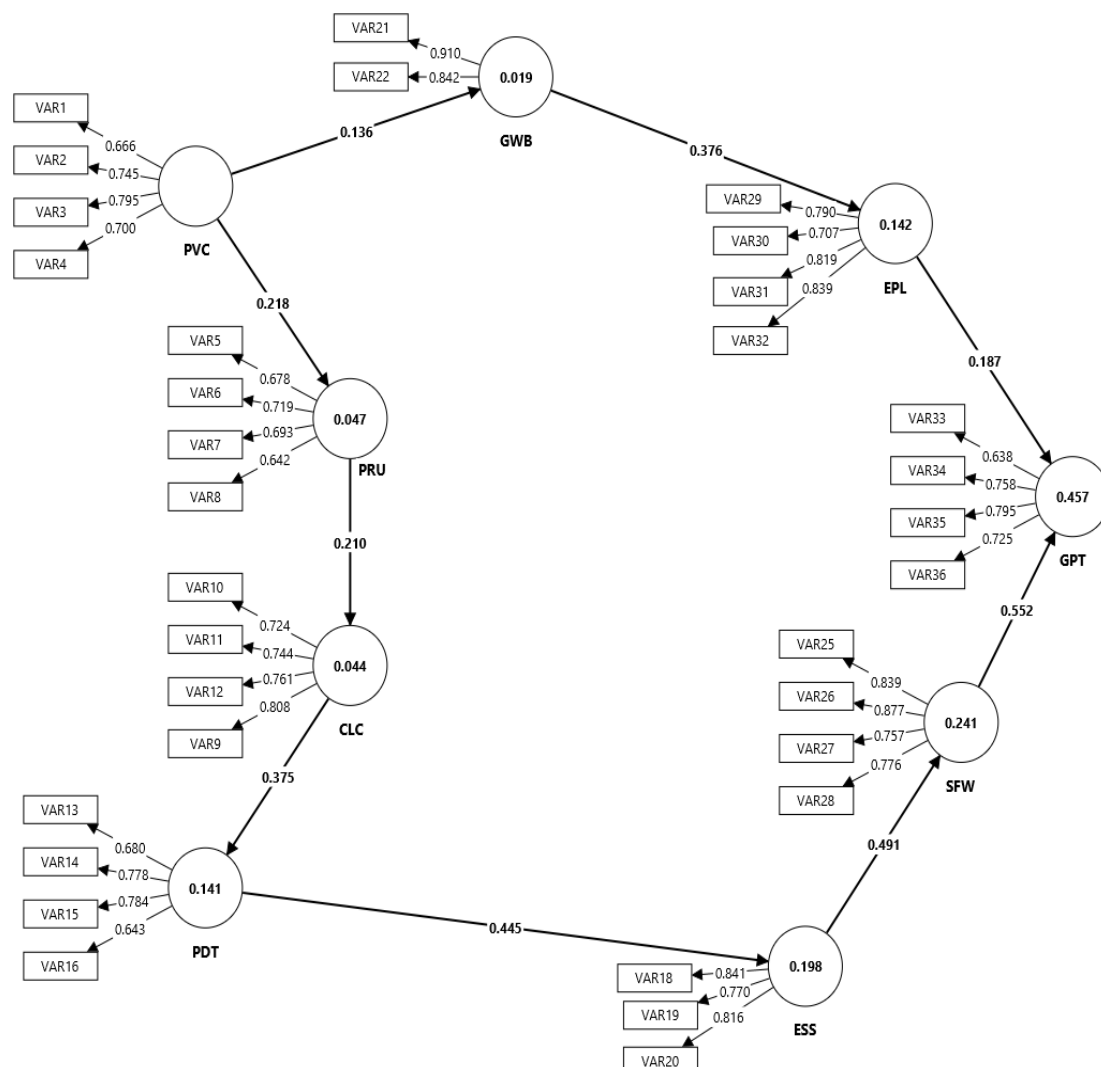
Table 6.4: Factor loadings of the measurement model

	CLC	EPL	ESS	GPT	GWB	PDT	PRU	PCV	SFW
VAR1								0.666	
VAR2								0.745	
VAR3								0.795	
VAR4								0.700	
VAR5							0.678		
VAR6							0.719		
VAR7							0.693		
VAR8							0.642		
VAR9	0.808								
VAR10	0.724								
VAR11	0.744								
VAR12	0.761								
VAR13						0.680			
VAR14						0.778			
VAR15						0.784			
VAR16						0.643			
VAR18			0.841						
VAR19			0.770						
VAR20			0.816						
VAR21					0.910				
VAR22					0.842				
VAR25									0.839
VAR26									0.877
VAR27									0.757
VAR28									0.776
VAR29		0.790							
VAR30		0.707							
VAR31		0.819							
VAR32		0.839							
VAR33				0.638					
VAR34				0.758					
VAR35				0.795					
VAR36				0.725					

Source: Author

The factor loadings directly impact the measured constructs' reliability and validity (Hair et al., 2019). The threshold for factor loadings in PLS-SEM is generally set to ensure that

indicators have a strong relationship with their corresponding latent constructs, thereby confirming convergent and discriminant validity. Most studies recommend a threshold of 0.708 for a good factor loading (Hair et al., 2019). Afthanorhan et al. (2020, p360) indicated that the minimum threshold should be 0.60 - "all the indicators of every construct were set using values of 0.60, which means the cut-off for the true value of factor loadings should be 0.60 per model." Of the 36 indicators, 33 were retained in the final measurement model. The other three indicators were excluded as they were lower than 0.60. These were VAR17 from ESS, VAR23, and VAR24 from GWB. The model generally had factor loadings higher than 0.60, with the majority above 0.70 (26 of the 33). Figure 6.2 depicts the measurement model.



Standardised Root Mean Square Residual, SRMR = 0.074

Figure 6.2: Measurement model with factor loadings

Source: Author

The goodness of fit indices are not as developed for PLS-SEM as in covariance-based structural equation modelling (CB-SEM), and the literature recommends caution if they are reported (Hair et al., 2019). Of all the indices of PLS-SEM, which include SRMR, d_{ULS} , d_G , Chi-square, and NFI (Ringle et al., 2024), the Standardised Root Mean Square Residual (SRMR) is the most developed index (Henseler et al., 2014). In this model, there is a good fit with $SRMR = 0.074$, better than both the conservative value of 0.080 (Hu & Bentler, 1998) and the recommended threshold of 0.10 (Henseler et al., 2014).

6.3.3.3 Internal consistency reliability

The internal consistency reliability was analysed with composite reliability, (ρ_C) and (ρ_A) and the Cronbach Alpha coefficient (α) and is indicated in Table 6.5. The composite reliability is used as it is weighted based on the construct indicators' individual loadings together with Cronbach Alpha, which is an unweighted measure (Hair et al., 2019). Despite these two measures, the final decision is made on composite reliability (ρ_A) as developed by Dijkstra and Henseler (2015) as a measure that is better than Cronbach alpha, which is conservative and unweighted, as well as composite reliability (ρ_C) which is considered too liberal (Hair et al., 2019). The results for ρ_C for all the dimensions ranging from 0.778 – 0.887, with the highest being SFW being $\rho_C = 0.887$, followed by EPL and GWB, both with the same $\rho_C = 0.869$. The lowest $\rho_C = 0.778$ for PRU.

Table 6.5: Internal consistency reliability with composite reliability and Cronbach Alpha

	Cronbach alpha	Composite reliability (ρ_A)	Composite reliability (ρ_C)
CLC	0.758	0.767	0.845
EPL	0.800	0.813	0.869
ESS	0.739	0.749	0.851
GPT	0.711	0.729	0.821
GWB	0.704	0.737	0.869
PDT	0.696	0.713	0.814
PRU	0.619	0.616	0.778
PCV	0.712	0.729	0.818
SFW	0.828	0.829	0.887

Source: Author

The Cronbach Alpha measures were all 0.70 and higher for all dimensions except for PRU, $\alpha = 0.619$. The Composite reliability (ρ_A) range for all the dimensions except for PRU range, $\rho_A = 0.713 – 0.829$. Hair et al. (2019) posit that higher reliability values are

good, with 0.70 to 0.90 deemed satisfactory to good. This is the range for all these dimensions except for PRU. Also noteworthy, these values were still lower than 0.95, which indicates that there are items that are redundant. PRU with values just over 0.60 are regarded as acceptable in exploratory research.

6.3.3.4 Convergence validity

The convergence validity was analysed with average variance extracted (AVE). The AVE provides a quantitative threshold to determine if the indicators of a construct are sufficiently correlated to represent the same underlying dimension. In this research, the highest AVE was that of GWB, with AVE = 0.769, followed by SFW with AVE = 0.662 and ESS with AVE = 0.655. This is reflected in Table 6.6. The only dimension with AVE less than 0.50 was PRU, with AVE = 0.467. Fornell and Larcker (1981), later supported by Hair et al. (2019), recommended a threshold of $AVE \geq 0.50$. Despite this threshold, some studies indicated that a lower AVE, but not lower than 0.40, may still indicate acceptable convergent validity if other criteria are met (Rubia, 2019).

Table 6.6: Convergence validity and internal consistency reliability

Dimension	Average variance extracted (AVE)
CLC	0.577
EPL	0.625
ESS	0.655
GPT	0.535
GWB	0.769
PDT	0.524
PRU	0.467
PCV	0.530
SFW	0.662

Note – PTB rounded to two decimals = 0.70

Source: Author

This was also confirmed by Safiih and Azreen (2016, p. 46), who stated that "the value of 0.4 is acceptable due to the condition that if AVE value is less than 0.5, but composite reliability is higher than 0.6, the convergent validity of the construct is acceptable" (Fornell & Lacker, 1981). As such, it can concluded that this model had an acceptable convergence validity.

6.3.3.5 Discriminant validity

Discriminant validity analyses whether the dimensions are distinct and measure different concepts. The Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT) are commonly used techniques to evaluate discriminant validity in PLS-SEM models. These methods help confirm that the constructs are not only reliable but also valid in distinguishing between different theoretical dimensions.

Fornell-Larcker criterion advanced that for discriminant validity to hold, the diagonal values (square root of AVE) should be greater than the correlations in their respective rows and columns. As indicated in Table 6.7, this was the case with the dimensions in this research. The values were higher (bold), ranging from 0.683 to 0.877. The square root of AVE for CLC (0.760) is greater than all correlations with other constructs in its row and column, satisfying the Fornell-Larcker criterion for CLC. The same is found with EPL (0.790), ESS (0.810), GPT (0.728), GWB (0.877), PRU (0.683), PTB (0.724), PCV (0.732) and SFW (0.814) (Table 6.7).

Table 6.7: Fornell-Larcker criterion for discriminant validity

	CLC	EPL	ESS	GPT	GWB	PDT	PRU	PCV	SFW
CLC	0.760								
EPL	0.423	0.790							
ESS	0.358	0.438	0.810						
GPT	0.429	0.500	0.448	0.732					
GWB	0.281	0.376	0.276	0.524	0.877				
PDT	0.375	0.263	0.445	0.300	0.237	0.724			
PRU	0.210	0.163	0.134	0.155	0.103	0.155	0.683		
PCV	0.168	0.166	0.189	0.110	0.136	0.230	0.218	0.728	
SFW	0.314	0.565	0.491	0.658	0.468	0.282	0.191	0.120	0.814

Source: Author

As such, each construct's square root of AVE is greater than its correlations with other constructs, suggesting that these constructs are distinct from one another and that the model has good discriminant validity. This was followed by cross-loading, which assessed whether an indicator's loading on its assigned target dimension (grey-shaded) was higher than its cross-loadings on other factors (Table 6.8).

Table 6.8: Cross-loading of indicators on dimensions

	PCV	PRU	CLC	PDT	ESS	GWB	SFW	EPL	GPT
VAR1	0.666	0.088	0.022	0.053	0.162	0.068	0.047	0.090	0.023
VAR2	0.745	0.176	0.205	0.205	0.157	0.092	0.129	0.193	0.141
VAR3	0.795	0.185	0.124	0.190	0.155	0.135	0.114	0.151	0.124
VAR4	0.700	0.157	0.097	0.175	0.086	0.086	0.036	0.028	-0.006
VAR5	0.113	0.678	0.187	0.110	0.022	-0.000	0.199	0.143	0.136
VAR6	0.187	0.719	0.089	-0.029	0.008	-0.040	0.027	0.087	0.020
VAR7	0.123	0.693	0.152	0.112	0.083	0.096	0.069	0.060	0.039
VAR8	0.170	0.642	0.143	0.216	0.238	0.212	0.210	0.148	0.212
VAR9	0.182	0.206	0.808	0.292	0.195	0.233	0.167	0.329	0.243
VAR10	0.098	0.179	0.724	0.229	0.284	0.178	0.266	0.293	0.299
VAR11	0.121	0.093	0.744	0.257	0.265	0.267	0.232	0.362	0.375
VAR12	0.105	0.150	0.761	0.345	0.346	0.186	0.293	0.311	0.395
VAR13	0.171	0.118	0.302	0.680	0.224	0.218	0.172	0.178	0.218
VAR14	0.194	0.089	0.220	0.778	0.354	0.084	0.215	0.124	0.231
VAR15	0.146	0.106	0.327	0.784	0.394	0.219	0.224	0.240	0.294
VAR16	0.163	0.144	0.231	0.643	0.291	0.163	0.202	0.213	0.101
VAR18	0.133	0.104	0.284	0.342	0.841	0.247	0.346	0.307	0.356
VAR19	0.106	0.042	0.229	0.328	0.770	0.150	0.354	0.240	0.345
VAR20	0.205	0.164	0.343	0.399	0.816	0.263	0.472	0.481	0.381
VAR21	0.094	0.096	0.259	0.250	0.240	0.910	0.415	0.383	0.414
VAR22	0.154	0.083	0.232	0.155	0.247	0.842	0.409	0.265	0.522
VAR25	0.087	0.181	0.240	0.184	0.366	0.395	0.839	0.514	0.562
VAR26	0.103	0.172	0.277	0.268	0.386	0.374	0.877	0.430	0.557
VAR27	0.036	0.143	0.187	0.250	0.371	0.333	0.757	0.431	0.545
VAR28	0.164	0.125	0.316	0.216	0.475	0.422	0.776	0.464	0.475
VAR29	0.082	0.079	0.315	0.188	0.328	0.301	0.452	0.790	0.411
VAR30	0.219	0.241	0.275	0.104	0.208	0.273	0.368	0.707	0.274
VAR31	0.139	0.157	0.394	0.238	0.413	0.327	0.493	0.819	0.455
VAR32	0.108	0.066	0.340	0.278	0.403	0.285	0.458	0.839	0.412
VAR33	0.149	0.056	0.196	0.193	0.210	0.431	0.358	0.313	0.638
VAR34	0.108	0.146	0.394	0.283	0.377	0.346	0.454	0.390	0.758
VAR35	0.103	0.120	0.350	0.257	0.382	0.395	0.598	0.395	0.795
VAR36	-0.025	0.123	0.294	0.139	0.314	0.381	0.479	0.359	0.725

Source: Author

This was done to ensure that each item or indicator loads more strongly on its intended construct than on others, thus supporting discriminant validity. The results show that all indicators are loaded strongly to their assigned target dimension compared to other indicators with different meeting recommendations of > 0.2 .

The Heterotrait-Monotrait Ratio (HTMT) was proposed by (Henseler et al., (2015) and advanced as the more reliable method. This method assesses the ratio of between-trait correlations to within-trait correlations. Table 6.9 provides the HTMT values of the model with the discriminant validity considered achieved if the HTMT values are below the recommended threshold of 0.85 ($H_{.85}$) (Kline, 2011) or a less conservative threshold of 0.90 ($H_{.90}$) recommended by (Henseler et al. (2015). The highest HTMT value is between PCV and SFW (0.841), which is close to but below the threshold of 0.85. All other HTMT values are well below 0.85, ranging from 0.159 to 0.689. Based on both these thresholds, the model achieved good discriminant validity.

Table 6.9: Heterotrait-Monotrait Ratio (HTMT) matrix for discriminant validity

	CLC	EPL	ESS	GPT	GWB	PDT	PRU	PCV	SFW
CLC									
EPL	0.542								
ESS	0.469	0.536							
GPT	0.576	0.649	0.600						
GWB	0.387	0.490	0.377	0.764					
PDT	0.505	0.340	0.602	0.412	0.329				
PRU	0.304	0.255	0.259	0.262	0.230	0.297			
PCV	0.217	0.235	0.255	0.205	0.191	0.307	0.311		
SFW	0.397	0.689	0.616	0.841	0.615	0.370	0.278	0.159	

Source: Author

Multiple methods are recommended to provide a comprehensive evaluation. Each method has its strengths and limitations, and using them in conjunction can offer a more robust discriminant validity assessment (Rönkkö & Cho, 2022). The present study employed this approach with the Fornell-Larcker criterion, cross-loadings and the Heterotrait-Monotrait Ratio (HTMT). The empirical analysis with the overall instrument, corrected item-total correlation, measurement evaluation with confirmatory tetrad analysis, factor loadings, convergence validity, composite reliability, and reliability, as well as discriminant validity, **support the proposition that operational uncertainty is a multi-dimensional construct.** What is evident from this reflective model is that all dimensions are manifestations of the underlying latent construct. This means that this multi-dimensional construct can be formed by these dimensions or other dimensions, and not all indicators need to be present to form the construct.

6.3.3.6 Validation of higher order construct – operational uncertainty

Before validation of HOC, descriptive statistics and reliability of the sustained performance were conducted as the outcome form part of the model. A detailed analysis of the percentile is presented in Figure 6.3.

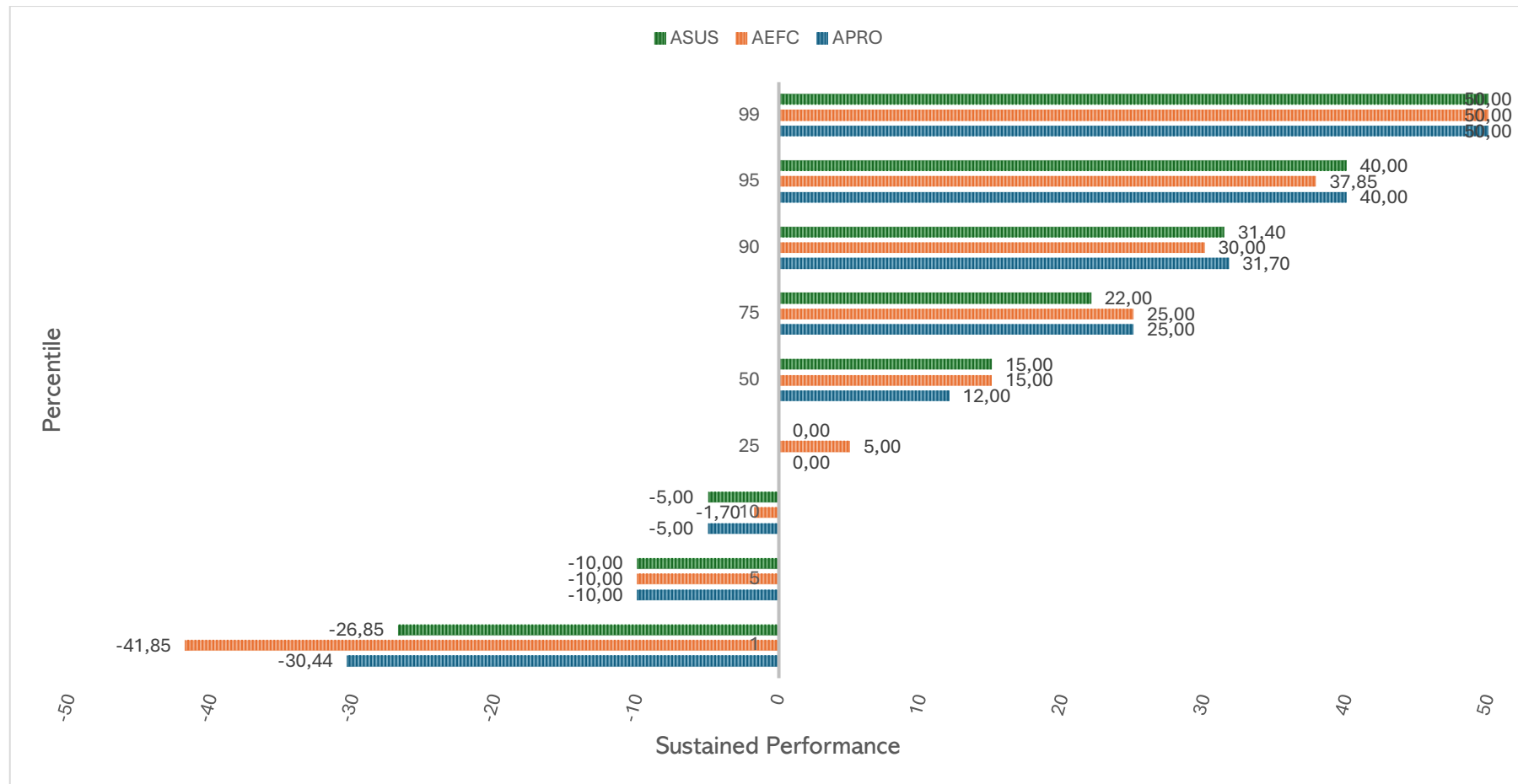


Figure 6.3: Description of the percentile of the sustained performance dimensions

Source: Author

The median score for APRO is $Mdn = 12.00$, slightly lower than for AEFC ($Md = 15.00$) and ASUS ($Mdn = 15.00$) (Table 6.10). At a 95% confidence interval for Mean PRO, 95% CI: $[10.16 - 14.07]$, while AEFC, 95% CI: $[11.25 - 15.60]$ and SUS, 95% CI: $[11.06 - 14.87]$. APRO, the skewness was -0.116 , with AEFC being -0.419 and SUS being -0.002 , while the kurtosis was for APRO (0.430), AEFC (1.722) and ASUS (0.623). The Cronbach alpha was $\alpha = 0.779$. In evaluating the effect of removing an item on overall reliability, APRO (0.779): Removing APRO increases reliability, indicating a potential improvement in internal consistency. AEFC (0.639): The removal of AEFC reduces reliability the most, indicating its strong contribution. Removal of ASUS (0.720): a moderate impact on reliability, slightly increasing when removed.

Table 6.10: Descriptive statistics of sustained performance dimensions

	Mean	95% Confidence Interval for Mean		5% Trimmed Mean	Median	Std. Deviation	Skewness	Kurtosis	Cronbach alpha if the item is deleted
		Lower Bound	Upper Bound						
APRO	12.11	10.16	14.07	12.15	12.00	16.065	-0.116	0.430	0.779
AEFC	13.16	11.25	15.06	13.41	15.00	15.637	-0.419	1.722	0.639
ASUS	12.96	11.06	14.87	12.82	15.00	15.646	-0.002	0.623	0.720

Overall Cronbach alpha, $\alpha = 0.790$

Source: Author

Figure 6.3 includes the percentile values for three dimensions of sustained performance: profitability (APRO), efficiency (AEFC) and sustainable practices (ASUS). A detailed analysis is presented in Figure 6.3, which includes the percentile values for these three dimensions of sustained performance: APRO, AEFC, and ASUS. For APRO, the 1st percentile is -30.44 (lower extreme), and the 5th percentile is -10.00 (improves significantly from the 1st percentile). At the 25th percentile, it was 0 , with the median (50th percentile) at 12.00 ; at the 75th percentile, it was 25.0 , and 50 at the 99th percentile. The same trend is evident for AEFC, with the 50th percentile at 15.00 , the 75th percentile at 25 , the 95th at 37.85 , and the 99th at 50 . Similarly ASUS with -26.86 at the 1st percentile, 0 at the 25th percentile, then 15 at the 50th percentile and 40 at the 95th percentile.

The reliability and validity of the LOC were first confirmed when determining the HOC. The measurement model was analysed, and the results show acceptable factor loadings, which ranged $\lambda = 0.598 - 0.866$. This is indicated in Table 6.11.

Table 6.11: Factor loadings of the LOCs

	CLC	EPL	ESS	GPT	GWB	PDT	PRU	PCV	SFW	SPF
AEFC										0.842
APRO										0.801
ASUS										0.868
VAR1								0.884		
VAR10	0.628									
VAR11	0.851									
VAR12	0.598									
VAR14						0.645				
VAR15						0.693				
VAR16						0.887				
VAR18			0.873							
VAR19			0.744							
VAR20			0.807							
VAR21					0.815					
VAR22					0.929					
VAR25									0.856	
VAR26									0.826	
VAR27									0.801	
VAR28									0.748	
VAR29		0.860								
VAR3								0.807		
VAR30		0.728								
VAR31		0.742								
VAR32		0.806								
VAR33				0.693						
VAR34				0.608						
VAR35				0.841						
VAR36				0.703						
VAR5							0.629			
VAR6							0.821			
VAR7							0.787			
VAR9	0.864									

Source: Author

The convergence validity and reliability were also confirmed with composite reliability (ρ_C) = 0.790 – 0.883, while composite reliability (ρ_A) = 0.631 – 0.870, and the AVE all above 0.5, ranged from 0.513 to 0.764. This is reflected in Table 6.12.

Table 6.12: Reliability and convergence validity of LOCs

	Cronbach's alpha	Composite reliability (ρ_A)	Composite reliability (ρ_c)	Average variance extracted (AVE)
CLC	0.758	0.864	0.829	0.555
EPL	0.800	0.870	0.865	0.617
ESS	0.739	0.762	0.850	0.655
GPT	0.711	0.725	0.806	0.513
GWB	0.704	0.802	0.866	0.764
PDT	0.650	0.804	0.790	0.561
PRU	0.615	0.644	0.793	0.563
PCV	0.609	0.631	0.835	0.717
SFW	0.828	0.848	0.883	0.654
SPF	0.790	0.816	0.876	0.702

Source: Author

The discriminant validity was also confirmed with the Heterotrait-Monotrait Ratio (HTMT) indicated in Table 6.13. The HTMT values of the model were all below the threshold of 0.90 ($H_{.90}$) (Henseler et al., 2015).

Table 6.13: Heterotrait-Monotrait Ratio (HTMT) for LOCs

	CLC	EPL	ESS	GPT	GWB	PDT	PRU	PCV	SFW	SPF
CLC										
EPL	0.542									
ESS	0.469	0.536								
GPT	0.576	0.649	0.600							
GWB	0.387	0.490	0.377	0.764						
PDT	0.474	0.336	0.642	0.395	0.288					
PRU	0.280	0.217	0.157	0.180	0.135	0.215				
PCV	0.152	0.220	0.271	0.199	0.191	0.216	0.230			
SFW	0.397	0.689	0.616	0.841	0.615	0.380	0.207	0.140		
SPF	0.129	0.155	0.232	0.181	0.120	0.132	0.117	0.172	0.178	

Source: Author

6.4 Segments of the data

The finite mixture analysis (FIMIX) was used to determine if hidden subsamples within the sample may create heterogeneity within the model. This model analysed three segments. These segments' named entropy statistic (EN) was greater than 0.50. The EN evaluates the quality of class separation or segmentation within a dataset (Table 6.14). An **entropy value greater than 0.50** is often considered important because it indicates sufficient separation between the latent classes (Sarstedt et al., 2011). Looking at AIC3 (modified AIC with Factor 3), the preferred segment is 3, with the lowest score for AIC3 = 739.02. This contrasts with the other important measure, CAIC (consistent AIC), which points to one segment with CAIC = 791.63. In evaluating the segment size, it was confirmed that all segments had more than 5% data to ensure that each segment had sufficient observations for meaningful and robust estimation. In this model, all segments had adequate data, with 70.0% for Segment 1, 19.7% for Segment 2, and 10.4% for Segment 3. A summed Fit was conducted with AIC3 and CAIC, and based on the results, the lowest value was for one segment (Summed Fit = 1547.58).

Table 6.14: Fit indices for segments for operational uncertainty based model

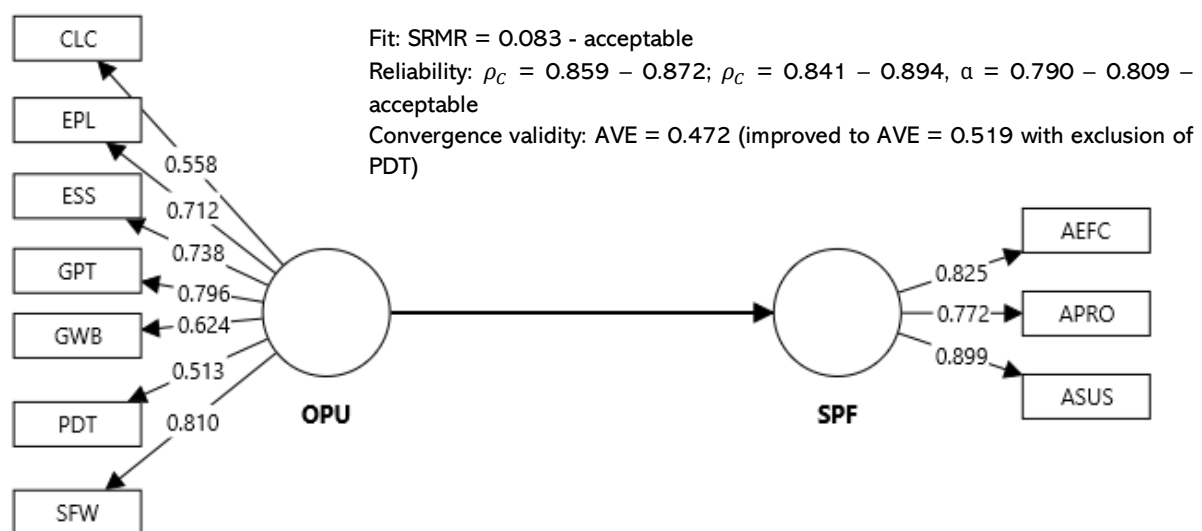
	1	2	3
AIC (Akaike's information criterion)	745.947	734.628	707.015
AIC3 (modified AIC with Factor 3)	755,947	755,628	739,015
AIC4 (modified AIC with Factor 4)	765.947	776.628	771.015
BIC (Bayesian information criterion)	781.630	809.564	821.202
CAIC (consistent AIC)	791,63	830,564	853,202
HQ (Hannan-Quinn criterion)	760.289	764.747	752.909
MDL5 (minimum description length with factor 5)	1004.364	1277.305	1533.950
LnL (LogLikelihood)	-362.973	-346.314	-321.507
EN (normed entropy statistic)	0.000	0.584	0.699
NFI (non-fuzzy index)	0.000	0.614	0.677
NEC (normalized entropy criterion)	0.000	109.006	78.883
Summed Fit	1547,577	1586,192	1592,217
%	0.700	0.197	0.104

Note: Discrete segment correlation - Max = 0.147

Source: Author

This is validated with the discrete segment assignment, and the result shows no meaningful correlation, with the largest being 0.147. If considering a meaningful correlation at ≥ 0.30 . As such, the data set show one segment and this is applied for the rest of the analysis.

To validate the HOC, the dimension scores of the dimensions (Latent Variables) were generated and used to develop the measurement model. This model was assessed using the same approach as that of the lower-order constructs, with the model having acceptable factor loading ($\lambda \geq 0.50$) for exploratory analysis (Hair et al., 2010). The HOC retained seven of the nine dimensions, though in the presence of PDT, the AVE = 0.472. This improved to 0.519 when removing PDT. The reliability was very good, and the discriminant validity was also good (Figure 6.4).



OPU – denoted as OPU1

Figure 6.4: Model for HOC

Source: Author

Operational uncertainty was, therefore, a higher-order construct based on the six or seven lower-order constructs, including CLC, EPL, ESS, GPT, GWB, (PDT), and SFW. In the research, operational uncertainty is measured as a reflective-reflective higher-order construct, which means that this construct remains intact when removing or replacing the LOCs.

6.5 Levels and structure of operational uncertainty in manufacturing

The second research proposition focused on whether operational uncertainty is a norm in manufacturing as not all relevant information is already known to decision-makers, and this proposition can be recapped as follows:

Proposition 2: Operational uncertainty is a norm in the manufacturing sector, as not all relevant information is already known to decision-makers

This was investigated with the relative importance index (RII), which identifies the most prevalent operational uncertainties, which are relatively important because they have the highest effect on manufacturing. This is followed by a determination of an operational uncertainty score to understand the level of uncertainty, which would guide the firms in developing effective response strategies. Flowing from this is the analysis of the interdependency relationship of the dimensions and visualising the structure of complex causal-effect relationships for optimal focus on the causal dimensions.

6.5.1 Relative importance index and levels of operational uncertainty

Table 6.15 indicates that PCV has the highest average, $\overline{RII}^* = 81.48\%$. This implies that growing geopolitical tension is the main reason for the operational uncertainty. This is followed closely by pandemic turbulence, e.g. COVID-19, PTB ($\overline{RII}^* = 78.99\%$), and cost of living-driven consumer behavioural change, CLC ($\overline{RII}^* = 78.95\%$). This was then followed by operational uncertainty of energy stability and security, ESS with $\overline{RII}^* = 76.29\%$. The fifth is the operational uncertainty from generational work behaviour and ethics, with $\overline{RII}^* = 74.56\%$, with the least rated being the entrenchment power of large firms, EPL with $\overline{RII}^* = 70.08\%$ and Skills for future work, SFW with $\overline{RII}^* = 70.46\%$.

Table 6.15: Relative Importance Index Analysis

Dimensions		$\overline{RII}^*$ (%)	Ranking
Process capability and variations	PCV	81.48	1
Policy and regulatory uncertainty	PRU	73.02	6
Cost of living-driven consumer behavioural change	CLC	78.95	3
Pandemic turbulence, e.g. COVID-19	PTB	78.99	2
Operational uncertainty of energy stability and security	ESS	76.26	4
Operational uncertainty from generational work behaviour and ethics	GWB	74.56	5
Skills for future work	SFW	70.46	8
The entrenchment power of large firms	EPL	70.08	9
Growing geopolitical tension	GPT	72.96	7

* - Based on the dimensions of the measurement model

Source: Author

6.5.2 Composite score of operational uncertainty

The research focused on nine dimensions for developing the operational uncertainty composite score. This is to determine the level of operational uncertainty in manufacturing based on the four levels of uncertainty. Courtney (2001), as supported by Millet (2002), highlighted four levels of uncertainty: a clear enough future or predictable outcomes, alternative futures, a range of futures, and true ambiguity. Level 1 represents the immediate and foreseeable future, while level 4 represents high uncertainty. Level 2 exists when there are clear paths forward based on a closed set of possible outcomes, and Level 3 occurs when the range of outcomes is larger and hence contributes to a range of futures. To determine this level, a four-step process was employed: (1) Step 1: identification of theoretical dimensions, (2) Step 2: Measurement indicators and determination of the level of individual factors, (3) Step 3: Determining the weight estimates of the factors and (4) Step 4: Determine the total composite score and the overall level of operational uncertainty. The nine dimensions of operational uncertainty contained four indicators. Therefore, the operational uncertainty composite score consists of 36 items (adjusted to 33 based on the measurement model results) that collectively focus on gaining knowledge of the level of operational uncertainty present in manufacturing. The final indicators were based on the inter-item correlation of the

individual indicators, Cronbach alpha for internal consistency reliability and measurement model. Table 6.16 presents the individual dimension score.

Table 6.16: The individual score of the dimensions of operational uncertainty

Dimension	Validity and Reliability [‡]	a_1	a_2	a_3	a_4	ξ_{sj}
PCV	Acceptable	4,26	3,72	4,06	4,25	81,5%
PRU	Acceptable	3,54	3,83	3,71	3,52	73,0%
CLC	Acceptable	4,06	3,86	3,93	3,94	79,0%
PTB	Acceptable	4,14	4,02	3,84	3,8	79,0%
ESS	Acceptable		3,97	3,77	3,69	76,2%
GWB	Acceptable	3,57	3,88			74,5%
SFW	Acceptable	3,51	3,51	3,65	3,43	70,5%
EPL	Acceptable	3,32	3,85	3,5	3,35	70,1%
GPT	Acceptable	4,01	3,56	3,44	3,59	73,0%

[‡]Acceptable based on inter-item correlation of the individual indicators, Cronbach alpha for internal consistency reliability, and measurement model.

Source: Author

Table 6.17 presents the weighted estimates for the dimensions. The results show that GWB has the largest weighted average (12.48%), followed by PRU with 12.18% and then PBT with 12.00%.

Table 6.17: Weighted estimates of the dimensions

	GPT	PRU	CLC	PBT	ESS	GWB	FW	EPL	PCV	Sum	SD	P_{ξ}	w_j
GPT	0,000	0,855	0,895	0,806	0,858	0,906	0,941	0,893	0,973	7,127	0,1596	1,1372	10,75%
PRU	0,855	0,000	0,862	0,818	0,893	0,949	0,811	0,836	0,875	6,899	0,1867	1,2876	12,18%
CLC	0,895	0,862	0,000	0,678	0,677	0,802	0,697	0,588	0,631	5,830	0,1813	1,0567	9,99%
PDT	0,806	0,818	0,678	0,000	0,584	0,825	0,733	0,746	0,763	5,953	0,2132	1,269	12,00%
ESS	0,858	0,893	0,677	0,584	0,000	0,919	0,496	0,575	0,572	5,574	0,2006	1,1183	10,57%
GWB	0,906	0,949	0,802	0,825	0,919	0,000	0,764	0,722	0,768	6,655	0,1983	1,3197	12,48%
SFW	0,941	0,811	0,697	0,733	0,496	0,764	0,000	0,460	0,363	5,265	0,2227	1,1725	11,09%
EPL	0,893	0,836	0,588	0,746	0,575	0,722	0,460	0,000	0,497	5,317	0,2192	1,1655	11,02%
PCV	0,973	0,875	0,631	0,763	0,572	0,768	0,363	0,497	0,000	5,442	0,1928	1,0492	9,92%

Source: Author

The lowest are PCV and CLC, which are 9.92% and 9.99%, respectively. The total composite score index the overall level of operational uncertainty was $MOUI_j = 0.752$, indicating the range of futures. As such, due to the complexity of the variables at play, it is not possible to divide these futures into a discrete and exhaustive set of possibilities; yet there are additional alternative futures that are crucial to the decision. In addition, the mechanisms that will bring about certain future conditions cannot be simply specified, making it impossible to calculate the precise probability of future events (Courtney, 2001; Millet, 2002; Walker et al., 2003). It is important for the manufacturing firm to understand the levels of uncertainty for effective decision-making (Walker et al., 2003).

6.6 Operational uncertainty on operations determinants

The operations determinants explained in Chapter 3 assessed how they are being influenced by the operational uncertainty dimensions. These include supply chain disruption (SCD), increase in the cost of production (ICP), market access restrictions (MAR), fluctuation of currency value (FCV), change in customer demand (CCD), restricted labour availability and productivity (RLA), quality of the product (QoP) and compromise knowledge management (CKM). The heatmap provides a detailed view of how each factor impacts each area, with darker colours indicating higher impacts (Figure 6.5).

The results show that the growing geopolitical tension (GPT) has a high impact on supply chain disruption (SCD), an increase in the cost of production (ICP), and market access restriction (MAR). Additionally, pandemic turbulence (PBT) impacts multiple areas significantly, especially SCD, ICP, and QoP. Cost-of-living-driven consumer change (CLC) has the highest impact on change in customer demand (CCD), indicating that consumer behaviour changes significantly in response to variations in living cost. Skills for future industrial work (SFW) and Process Capability and Variations (PCV) have a high impact on compromise knowledge management (CKM), suggesting that knowledge management is particularly affected by skill requirements and process consistency.

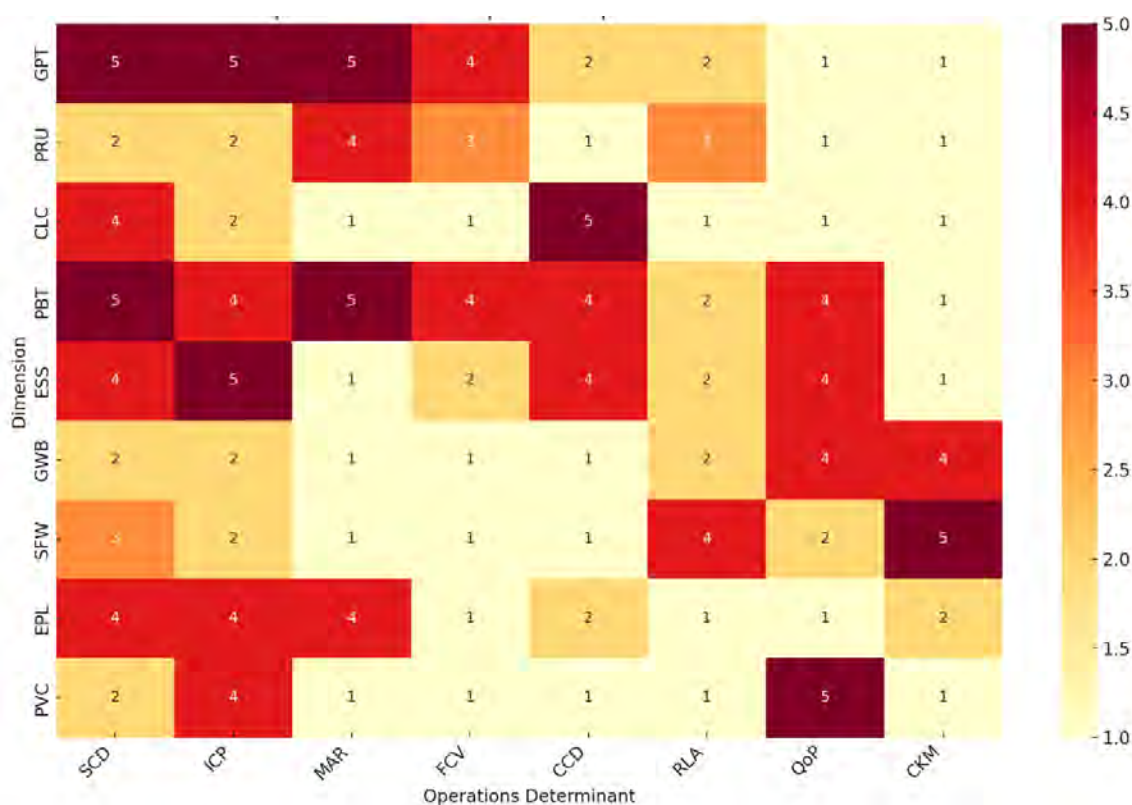


Figure 6.5: Heatmap of dimensions (factors) on operations determinants (impact areas)

Source: Author

6.7 Chapter conclusion

This chapter investigated the first objective of the study, which focused on comprehensively understanding operational uncertainty within manufacturing. Two critical propositions were developed to investigate this objective based on the research gaps highlighted in Chapter 3. In testing these propositions, the analysis was based on empirical data from both the firm survey and experts. The first proposition tested operational uncertainty as a multi-dimensional construct. The results provided insights and confirmed the multidimensionality of operational uncertainty, retaining all theoretically proposed dimensions. This was evident from the corrected item-total correlation and reliability of the instrument.

Detailed analysis was then conducted with the measurement from PLS-SEM, which was acceptable based on the factor loadings, model fit, convergence validity, composite reliability, and discriminant validity. This confirmed and supported the proposition. Of

note was that the model was confirmed as being reflective, meaning it can have items and dimensions that are interchanging, added, or removed based on a context.

The second proposition of the study tested that operational uncertainty was a norm in manufacturing. This analysis was conducted by first understanding the relative importance index, which identified the most prevalent uncertainty, and then understanding these levels, which are critical for responding to and managing these operational uncertainties. The most prevalent operational uncertainty from the firm survey was growing geopolitical tension, pandemic turbulence, cost of living-driven consumer behavioural change and operational uncertainty of energy stability and security.

The composite score from the MOUI indicated that the operation can be categorised as a range of futures. This further confirmed that operational uncertainty is a norm in manufacturing. This underlines that there is a complexity of operational uncertainty dimensions at play; thus, it was not possible to divide these futures into a discrete and exhaustive set of possibilities. Thus, the mechanisms that will bring about certain future conditions cannot be simply specified, making it impossible to calculate the precise probability of future events.

The results also highlight that growing geopolitical tension has a high impact on supply chain disruption, resulting in an increase in the cost of production, while cost-of-living-driven consumer change highly impacts change in customer demand, suggesting that consumer behaviour changes significantly in response to variations in living cost. Skills for Future Work and process capability and variations also compromise knowledge management. The next chapter provides the results of the analysis of the capabilities of Industry 4.0 and 5.0 technologies to manage these operational uncertainties.

Chapter 7

Capabilities of Industry 4.0 and 5.0 Technologies to Manage Operational Uncertainty

7.1 Introduction

Manufacturing firms are currently undertaking digital transformation initiatives to respond to operating environmental challenges, sustainability imperatives (David et al., 2022; (Kibe et al., 2023), and the need to enhance the firm's competitive advantage (Lorenz et al., 2020; Saabye et al., 2022). This involves cultivating the capacity of firms to effectively embrace Industry 4.0 and Industry 5.0 technologies, which serve as a crucial catalyst for driving firm performance (Arcidiacono et al., 2023). As such, Industry 4.0 and 5.0 technologies can be critical conditions - "variable" in developing the configurations. Thus, objective 2 of the study focused on reviewing and validating the capabilities of Industry 4.0 and Industry 5.0 technologies in manufacturing operations and the linkage of these capabilities to organisational learning. This was done by analysing the technologies used in Industry 4.0 and 5.0 and the association between the technologies and the industry. In addition, study results validate the capabilities of Industry 4.0 and 5.0 technologies and the heatmap of their capabilities from experts in line with proposition 3. The chapter concludes by analysing the relationship between Industry 4.0 and 5.0 with organisational learning in line with proposition 4.

7.2 Industry 4.0 and 5.0 technologies in use in the manufacturing sector

Table 7.1 provides a categorisation overview of how each technology is currently being utilised in the manufacturing sector. The threshold of 40% or less represents low use, over 40% up to 70% represents moderate use, and more than 70% represents high use. Technologies such as IoT, AI, and BDA were highly used, with over 70% of respondents indicating strong usage of these technologies in the manufacturing sector, with the IoT at 87.4%, followed by BDA at 71.4%, then AI at 70.6%. The results of this research show that advanced robotics (ARB) has moderate usage (56.9%), suggesting it

is somewhat used but not as widely as IoT, AI, or BDA. Blockchain (14.1%), AR/VR (32.1%), ADM (17.9%), and QCP (19.8%) are in the low-use category.

Table 7.1: Level of Industry 4.0 and 5.0 technologies used in the manufacturing sector

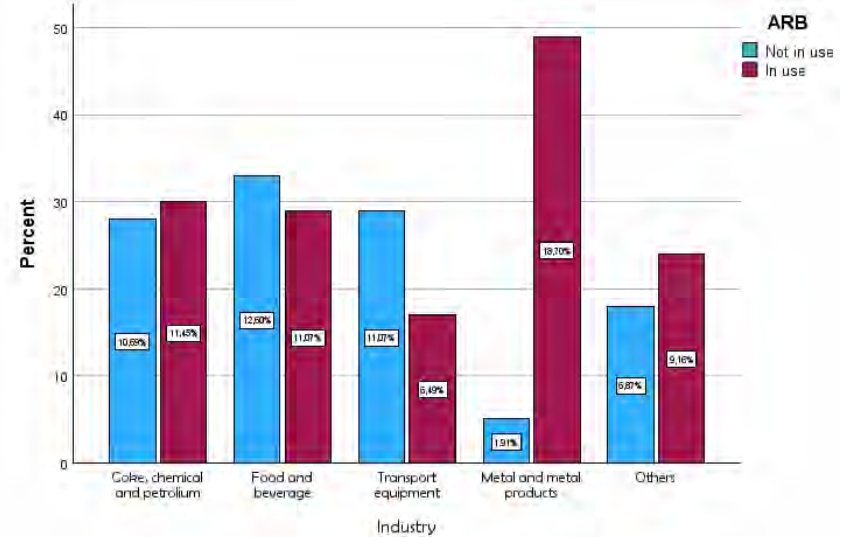
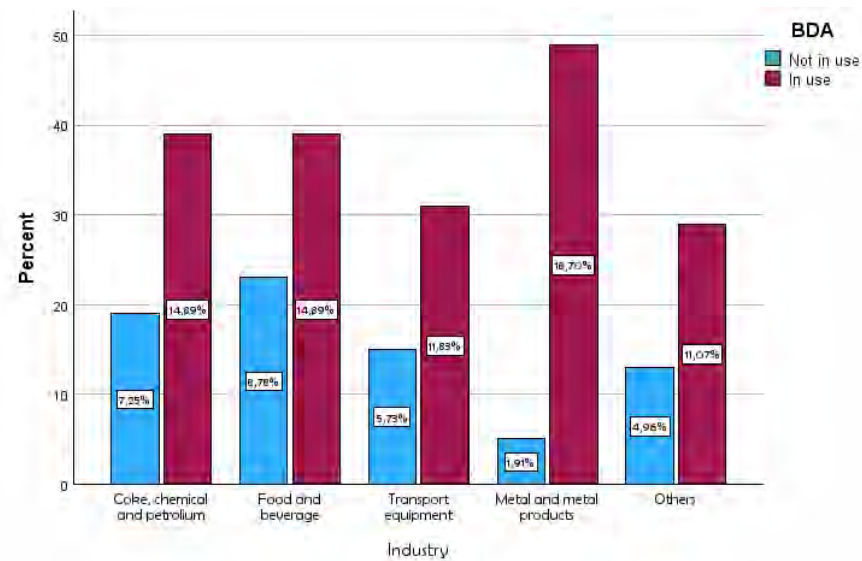
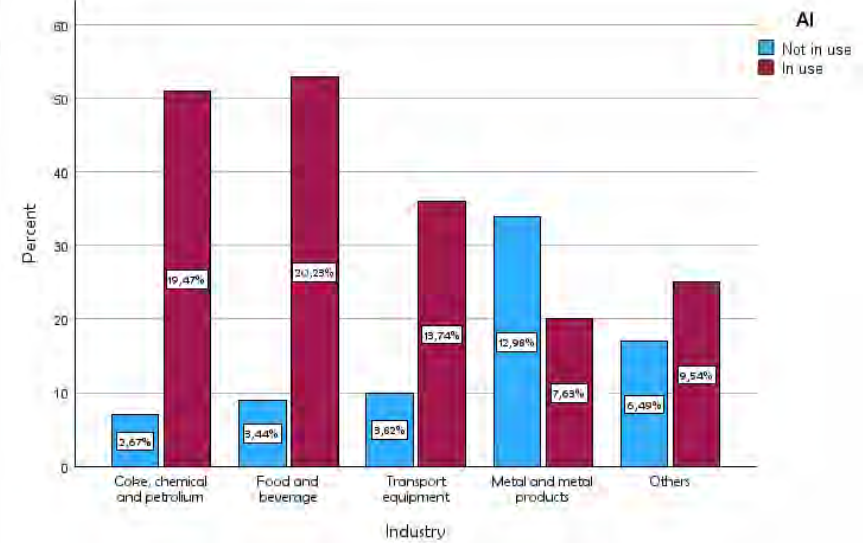
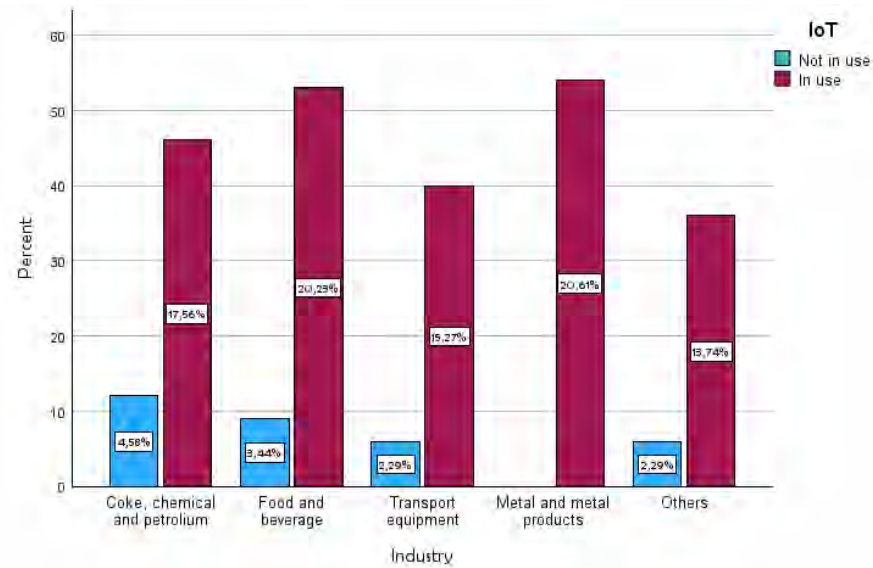
Technology	Usage	N	%	Level of use
IoT	Not in use	33	12.6%	High use
	In use	229	87.4%	
AI	Not in use	80	30.5%	High use
	In use	185	70.6%	
BDA	Not in use	77	29.4%	High use
	In use	187	71.4%	
ARB	Not in use	75	28.6%	Moderate use
	In use	149	56.9%	
BCC	Not in use	225	85.9%	Low use
	In use	37	14.1%	
AR/VR	Not in use	178	67.9%	Low use
	In use	84	32.1%	
ADM	Do not use	215	82.1%	Low use
	Use	47	17.9%	
QCP	Do not use	210	80.2%	Low use
	Use	52	19.8%	

Note: ≤ 40% (Low use), 41- 70% (moderate use), greater than 70% (high use)

Source: Author

7.3 Association between technologies and industry

All industries shown in the cluster plots in Figure 7.1 have a high level of IoT usage, indicated by the large dark red bars, suggesting that IoT has substantial penetration across the manufacturing industries.



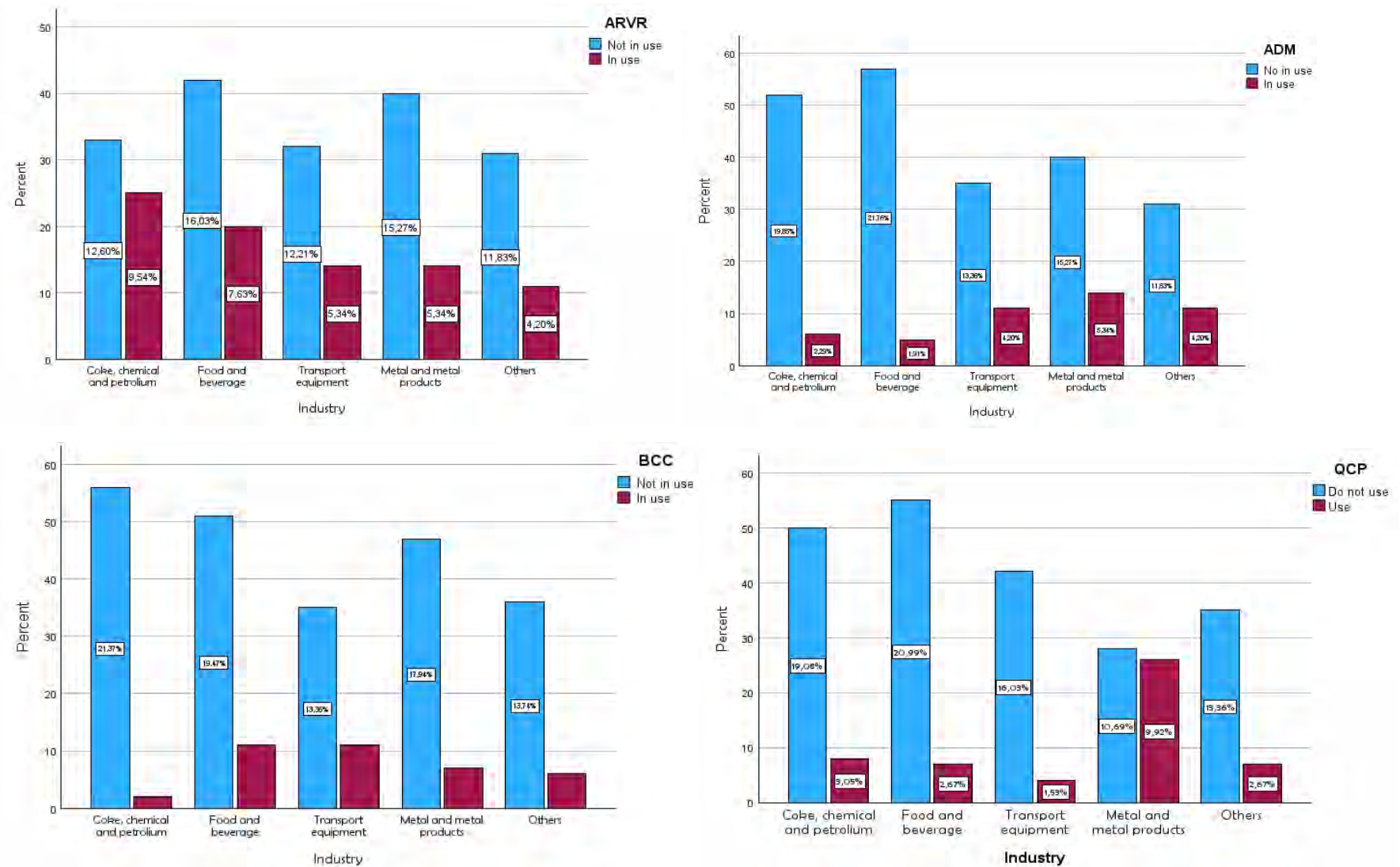


Figure 7.1: Cluster plots of industries with technology use

Source: Author

The percentage of IoT in use in each industry is much higher than the percent of "Not in use," indicating that IoT technology is widely used. Based on the total sample for the food and beverage industry, "in use" is 20.23%, with a not-in-use (3.44%). The need for real-time monitoring and automation in food processing and safety may drive this high adoption. For the coke, chemical and petroleum industries, 17.56% of firms use IoT, while 4.56% do not use IoT. In analysing the transport equipment industry, the results show that 15.27% was in use while 2.29% was not in use. In the metal and metal products industry, IoT use is 20.61%, with a not-in-use rate of 2.29%, demonstrating high use, possibly for production monitoring and quality control. Others show use of 13.74% compared to 2.29% "Not in use." This might suggest more varied use across different sectors that are not individually specified

The cluster plot for AI shows that the "in use" category is generally higher than "not in use" in most industries. The food and beverage industry has the highest AI usage, followed by the coke, chemical, and petroleum industries. However, the metal and metal products industry has a relatively balanced distribution between AI "in use" and "not in use." The trend started to change with the metal and metal products industry (MMP) having higher use for BDA and ARB, while more balanced "in use" and "not in use" for ARB for coke, chemical and petroleum (CCP), food and beverage (FAB), and transport equipment. The 'not in use' is higher than "in use" for ARVR, ADM, BCC and QCP.

Table 7.2 provides a Chi-square of association with significance and Bonferroni correction for standardised adjusted residuals. This analysis provides insights into technologies' and industries' associations and effect sizes, particularly emphasising statistically significant relationships. Seven of the eight Industry 4.0 and 5.0 technologies were statistically significant, reduced to three after Bonferroni correction to minimise Type I error. The statistically significant were AI, ARB, and QCP. As such, after applying the Bonferroni correction, the adjusted residuals show that food and beverage (FAB), coke, chemical and petroleum (CCP), and metal and metal products (MMP) categories contribute notably to this association.

Table 7.2: Chi-square of association with significance and Bonferroni correction for standardised adjusted residuals

	Chi-square	<i>p</i> -value	Cramer's V	Adj res*
IoT	11.56	0.021	0.21	
AI	48.11	<0.001*	0.429	CCP, FAB, MMP
BDA	13.04	0.011	0.223	
ARB	35.90	<0.001*	0.370	TEQ, MMP
BCC	9.815	0.044	0.194	
AR/VR	4.901	0.298		
ADM	11.78	0.019	0.212	
QCP	35.24	<0.001*	0.367	MMP

* Significant Post Bonferroni correction with corrected alpha = 0.005

Source: Author

The AI has a statistically significant association with industry ($\chi^2 = 48.11$, $p < 0.001$) with moderate strength where the Cramer's V, $\phi = 0.429$. Additionally, ARB has a statistically significant association with industry ($\chi^2 = 35.90$, $p < 0.001$) with moderate strength, $\phi = 0.370$. Also, QCP has a statistically significant association with industry ($\chi^2 = 35.24$, $p < 0.001$) with moderate strength, $\phi = 0.367$.

7.4 Validating Industry 4.0 and 5.0 technologies capabilities

Table 7.3 indicates further descriptive statistics and Cronbach alpha of indicators of capabilities of Industry 4.0 and 5.0 technologies. The mean values for all indicators (IMT1 to IMT20) range from $M = 3.64$ to 3.91 , showing a moderately high level of agreement on the capability of Industry 4.0 and 5.0 technologies in all indicators. The indicators have a 95% confidence interval, showing the range within which the true mean is likely to fall. The intervals are relatively narrow, suggesting stability in the data and high confidence in the reported mean values. The 5% trimmed mean and median are close to each other and to the mean for each item. This suggests that the data are relatively symmetric with minimal outliers, as the trimmed mean would otherwise differ significantly from the untrimmed mean. The indicators with the highest mean values reflect the strongest perceived capabilities or agreement with statements about Industry 4.0 and 5.0 technologies, IMT18 (Mean = 3.91 , SD = 0.797), Mdn = 4.0 . IMT18 indicated agreement or high perceived capability. It is followed by IMT19 ($M = 3.90$, SD = 0.914) and a median, Mdn = 4.00 , then IMT5 (Mean = 3.89 , SD = 0.844). The indicators with the lowest mean values reflect relatively lower agreement with statements about Industry 4.0 and 5.0 technologies, including IMT15 ($M = 3.64$, SD = 0.960), followed by IMT13

(Mean = 3.74, SD = 0.897) and IMT17 (Mean = 3.74, SD = 0.854). Most items show a negative skew, indicating a slight tendency for responses to lean towards higher values (i.e., toward agreement or higher capability levels). Skewness ranged from -1.015 to -0.475. The kurtosis values varied, with some indicators showing slightly positive kurtosis while others were slightly negative. The range for kurtosis was -0.488 to 1.061. Skewness and kurtosis were within ± 2 , indicating that the data were normally distributed.

The overall Cronbach alpha coefficient ($\alpha = 0.886$) indicates a high internal consistency in all items. A Cronbach's alpha above 0.8 is generally considered very good based on the guidelines of Pallant (2020). Cronbach's alpha values for the six dimensions ranged from $\alpha = 0.615$ to 0.774. Based on the minimum acceptable value of 0.6 by Hair et al. (2010), the dimensions had an acceptable internal consistency reliability. The dimensions were scenario planning and future prediction (SPFP) (IMT1 -IMT3), Supply chain integration and collaboration (SCIC) (IMT 4 – IMT6), and Flexible production and mass customisation (IMT7 - IMT8).

The others are the real-time system and process monitoring and response (RPMR) (IMT9 – IMT14), root cause analysis and sustainable solutions (RCAS) (IMT15 - IMT17), and protective ecosystem (humans and systems) (PEHS) (IMT18 – IMT20)

Table 7.3: Descriptive statistics and Cronbach alpha of indicators of capabilities of Industry 4.0 and 5.0 technologies

	Mean (M)	95% Confidence Interval for Mean		5% Trimmed Mean	Median (Mdn)	Std. Deviation (SD)	Skewness	Kurtosis	Cronbach alpha (α)
		Lower Bound	Upper Bound						
IMT1	3.84	3.72	3.96	3.90	4.00	0.984	-0.533	-0.291	0.615
IMT2	3.76	3.65	3.88	3.84	4.00	0.970	-1.010	1.061	
IMT3	3.78	3.67	3.90	3.84	4.00	0.940	-0.752	0.341	
IMT4	3.85	3.74	3.95	3.90	4.00	0.844	-0.822	0.889	0.727
IMT5	3.89	3.77	4.00	3.95	4.00	0.948	-0.857	0.523	
IMT6	3.76	3.65	3.86	3.80	4.00	0.863	-0.804	0.590	
IMT7	3.76	3.66	3.87	3.80	4.00	0.847	-0.708	0.228	0.620
IMT8	3.83	3.73	3.93	3.87	4.00	0.799	-0.597	0.397	
IMT9	3.76	3.64	3.87	3.79	4.00	0.968	-0.567	-0.488	0.729
IMT10	3.79	3.68	3.89	3.82	4.00	0.875	-0.743	0.157	
IMT11	3.76	3.64	3.87	3.78	4.00	0.919	-0.630	-0.349	
IMT12	3.73	3.62	3.84	3.76	4.00	0.879	-0.737	0.206	
IMT13	3.74	3.64	3.85	3.80	4.00	0.897	-1.015	1.025	
IMT14	3.77	3.68	3.87	3.81	4.00	0.811	-0.738	0.699	0.774
IMT15	3.64	3.52	3.75	3.67	4.00	0.960	-0.684	-0.168	
IMT16	3.76	3.65	3.86	3.80	4.00	0.836	-0.863	0.854	
IMT17	3.74	3.64	3.84	3.78	4.00	0.854	-0.776	0.414	0.755
IMT18	3.91	3.81	4.01	3.95	4.00	0.797	-0.475	-0.073	
IMT19	3.90	3.79	4.01	3.95	4.00	0.914	-0.764	0.065	
IMT20	3.83	3.71	3.95	3.90	4.00	0.980	-0.815	0.529	

Cronbach Alpha coefficient, $\alpha = 0.886$

Source: Author

7.5 Management of operational uncertainty impact with Industry 4.0 and 5.0 technologies

Grounded on the theoretical perspective (Chapter 3), the experts were asked to provide input as to the capabilities of Industry 4.0 and 5.0 technologies in managing operational uncertainty. The third proposition of the research focused on Industry 4.0 and 5.0 technology capabilities to manage operational uncertainty. This proposition can be recapped as follows.

Proposition 3: Industry 4.0 and 5.0 technologies capabilities can manage operational uncertainty in the manufacturing sector.

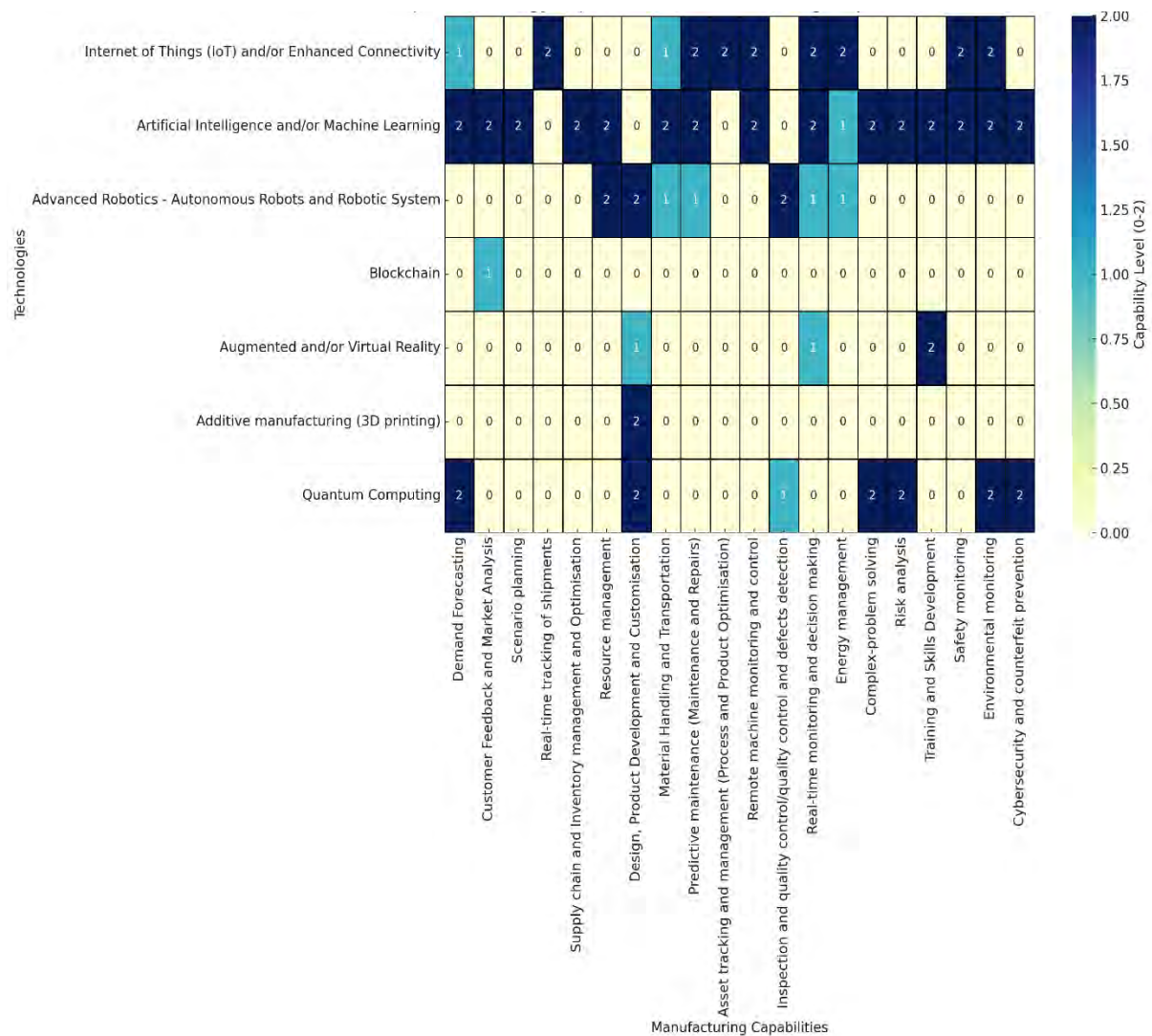
These experts initially assessed the operations determinants influenced by the operational uncertainty (section 6.6) and then the capabilities of the Industry 4.0 and 5.0 technologies to improve the initiatives necessary to respond to the impacts of the operational uncertainty;

7.5.1 Management of operations determinants

Figure 7.2 provides the experts' view on managing operations determinants from operational uncertainty dimensions with capabilities of Industry 4.0 and 5.0 technologies. Artificial intelligence (AI) has the highest capability level in most manufacturing requirements. It scores a 2 (fully capable) for critical functions such as Demand Forecasting, Customer Feedback and Market Analysis, Scenario Planning, Supply Chain and Inventory Management, Resource Management, Predictive Maintenance, and Real-Time Monitoring.

The Internet of Things (IoT) is the second most broadly capable Industry 4.0 and 5.0 technologies and is particularly effective in real-time tracking of Shipments, Predictive Maintenance, Asset Tracking and management, and Remote Machine Monitoring and control, all of which have full capability levels. It is followed by advanced Robotics (Autonomous Robots and Robotic Systems) that are fully capable (2) for tasks like Design, Product Development, and Customisation and Inspection and Quality Control. This was followed by quantum Computing, which showed full capability (2) for Demand Forecasting, Design and Product Development, Complex-Problem Solving, Risk Analysis,

Environmental Monitoring, and Cybersecurity. Additive Manufacturing (3D Printing) was shown to be fully capable (2) for Design, Product Development, and Customisation. Augmented and Virtual Reality (AR/VR) showed full capacity (2) for Training and Skills Development, indicating its strength in immersive training and skill building. Blockchain shows limited full capabilities, with a 1 (Partially capable) for customer feedback and Market Analysis.



** - Big data analytics missing and not evaluated due non-visibility of the column

Figure 7.2: Heatmap on the management of operations determinants

Source: Author

These results support proposition 3, that Industry 4.0 and 5.0 technologies can manage operational uncertainty in the manufacturing sector.

7.6 Capabilities of Industry 4.0 and 5.0 and organisational learning

The fourth research proposition focused on organisational learning has a relationship with the capabilities of Industry 4.0 and 5.0 technologies as it is theorised to improve the effectiveness of the capabilities implemented by Industry 4.0 and 5.0 technologies. This proposition can be recapped as follows.

Proposition 4: Organisational learning has a positive relationship with the capabilities of Industry 4.0 and 5.0 technologies

7.6.1 Descriptive statistics

Table 7.4 presents the descriptive statistics of organisational learning (OLN1- OLN9). The mean values for the indicators (OLN1 to OLN9) were $M = 3.34 - 4.02$. The indicators with the highest mean were OLN1 ($M = 4.02$, $SD = 0.835$), OLN3 ($M = 3.97$, $SD = 0.844$) and OLN2 ($M = 3.96$, $SD = 0.859$). The median for these statements was $Mdn = 4.00$. This highlights that the participants who agreed most with the statements. The statements the participants least agreed with were OLN8 ($M = 3.34$, $SD = 0.696$) and OLN9 (Mean = 3.39, $SD = 0.702$). These indicators with the lowest mean values indicate comparatively lower levels of agreement with the statements. In this data, the skewness values range from -1.252 (OLN6) to -0.385 (OLN9). The 5% trimmed mean values are generally close to the regular mean values for each indicator, indicating that there were probably a few outliers in the data. The skewness values are all negative, indicating a consistent tendency for responses to lean towards higher values (positive ratings). Kurtosis range was -0.218 (OLN2) to 2.013 (OLN6). This range of skewness was within ± 2 with the kurtosis slightly above, and the results indicated normally or near normally distributed data (Hair et al., 2010).

Table 7.4: Descriptive statistics of organisational learning

	Mean	95% Confidence Interval for Mean		5% Trimmed Mean	Median (Mdn)	Std. Deviation (SD)	Skewness	Kurtosis
		Lower Bound	Upper Bound					
OLN1	4.02	3.92	4.12	4.09	4.00	0.835	-0.880	0.951
OLN2	3.96	3.85	4.06	4.01	4.00	0.859	-0.577	-0.218
OLN3	3.97	3.87	4.07	4.02	4.00	0.844	-0.598	-0.112
OLN4	3.89	3.79	3.99	3.94	4.00	0.857	-0.668	0.193
OLN5	3.62	3.53	3.71	3.65	4.00	0.721	-0.961	1.420
OLN6	3.64	3.55	3.73	3.68	4.00	0.728	-1.252	2.013
OLN7	3.46	3.37	3.55	3.49	4.00	0.714	-0.564	0.357
OLN8	3.34	3.25	3.42	3.38	3.00	0.696	-0.634	0.330
OLN9	3.39	3.31	3.48	3.42	3.00	0.702	-0.385	0.293

Source: Author

These indicators had a good internal consistency reliability with $\alpha = 0.847$. If indicators are removed individually, the overall internal consistency reliability will still range from 0.821 – 0.840, showing minimal change in the reliability of the scale (Table 7.5). The corrected item-total correlation was also acceptable, with a range of 0.468 – 0.653.

Table 7.5: Internal consistency reliability of organisational learning

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
OL1	29,27	17,156	,587	,414	,828
OL2	29,34	16,599	,653	,548	,821
OL3	29,32	17,423	,536	,410	,834
OL4	29,40	16,970	,595	,424	,828
OL5	29,67	17,486	,648	,494	,823
OL6	29,65	18,051	,538	,390	,833
OL7	29,83	18,523	,468	,308	,840
OL8	29,96	18,071	,567	,407	,831
OL9	29,90	18,504	,483	,367	,839

Overall reliability for all indicators (nine indicators) $\alpha = 0.84$

Source: Author

Table 7.6 shows the Pearson correlation analysis that indicates that there was a statistically significant positive correlation with five of the the six dimensions of Industry 4.0 and 5.0 capabilities response to operational uncertainty in manufacturing operations. With a statistically significant positive correlation between SPFP and OLN of $r = 0.268$, $p < .01$. There was also a statistically significant positive correlation between SCIC and OLN, $r = 0.260$, $p < .01$ for FPMC with $r = 0.213$, RCAS and ONL with $r = 0.292$ and for PEHS and OLN $r = 0.267$, $p < 0.1$. There is no statistically significant correlation between RPMR and OLN. The results support proposition 4 of the study, in that the **organisational learning has a positive relationship with the capabilities of the of Industry 4.0 and 5.0 technologies.**

Table 7.6: Correlation matrix of Industry 4.0 and 5.0 capabilities response to operational uncertainty in manufacturing operations

	OLN	SPFP	SCIC	FPMC	RPMR	RCAS	PEHS
OLN							
SPFP	,268**						
SCIC	,260**	,569**					
FPMC	,213**	,386**	,446**				
RPMR	0.024	0.048	0.104	0.046			
RCAS	,292**	,403**	,337**	,281**	-0.035		
PEHS	,267**	,288**	,178**	,188**	-0.065	,654**	
**. Correlation is significant at the 0.01 level (2-tailed).							

Source: Author

7.7 Chapter conclusion

The chapter provided insights into reviewing and validating the capabilities of fourth— and fifth-industrial revolution technologies in manufacturing operations. In providing a categorisation overview of how each technology is currently being utilised in the manufacturing sector, the findings revealed that the Internet of Things, artificial intelligence, and big data analytics were in high use while advanced robotics were in moderate use. During the time of the study, blockchain, augmented and virtual reality, additive manufacturing (3D printing), and quantum computing were in low use in the manufacturing sector. Furthermore, the findings revealed that Artificial intelligence (AI)

has the highest capability level in most manufacturing requirements. It was followed by the Internet of Things (IoT) as the second most broadly capable Industry 4.0 and 5.0 technologies and is particularly effective in real-time tracking of Shipments, Predictive Maintenance, Asset Tracking and management, and Remote Machine Monitoring and control. It is followed by advanced Robotics (Autonomous Robots and Robotic Systems) and then quantum computing. Augmented and Virtual Reality (AR/VR) showed full capacity for Training and Skills Development, indicating its strength in immersive training and skill building, while Blockchain shows limited full capabilities for customer feedback and market Analysis.

Chapter 8 Configurations for Sustained Performance in Manufacturing

8.1 Introduction

Objective one of the research developed a comprehensive understanding of operational uncertainty in manufacturing testing propositions. This supported the notion that operational uncertainty is a multidimensional construct and that it is a norm in the manufacturing sector, with results showing higher levels of operational uncertainty. This validated the need to develop solutions to respond to operational uncertainty. Flowing from Chapter 6 was the reviewed and validation in Chapter 7 of the capabilities of fourth and fifth industrial revolution technologies in manufacturing operations. The present chapter investigates objective 3 using propositions five and six. This objective formulates and analyses sustainable performance configurations (outcomes condition) with causal conditions from operational uncertainty, Industry 4.0 and 5.0 technologies, and organisational learning.

Configurations in manufacturing using fuzzy set qualitative comparative analysis (fsQCA) are instrumental in identifying complex causal relationships by allowing research to explore multiple pathways and conditions that lead to specific outcomes (Cangialosi, 2023; Schneider & Wagemann, 2012). These configurations are built with a combination of conditions, which refers to the relationship between a construct that explains the outcome and a construct or dimension that the conditions describe based on their set membership (Ragin, 2009). The optimum solutions were developed from the combination of a 4-step process discussed earlier (in methodology chapter 4):

Step 1: Selection and validation of the causal conditions of operational uncertainty with fuzzy-DEMATEL.

Step 2: Build configuration

Step 3: Causal conditions-based PLS-SEM measurement and structural models

Step 4: Develop configurations - solutions (fsQCA)

The fifth and the sixth propositions of the study can be recapped as follows:

Proposition 5: The combinations of OPU, IRT, and OLN conditions lead to high or low sustained performance.

Proposition 6: Integration of optimising methods is necessary for optimum outcomes of QCA-based methods.

8.2 Fuzzy-DEMATEL

The research adapted its approach from Lin and Wu (2008) and (Yeh & Huang, 2014) adding consistency measures for the DEMATEL Method from Shieh and Wu (2016), by creating seven sub-steps.

Step 1: Decision goals, set of criteria, and decision-makers

The goal of the decision is to determine the relationship and interdependence of the factors. This is based on nine operational uncertainty dimensions, which are used as sets of criteria (Table 8.1).

Table 8.1: Dimensions of operational uncertainty

Dimensions	
Growing geopolitical tension	GPT
Policy and regulatory uncertainty	PRU
Cost of living-driven consumer behavioural change	CLC
Pandemic turbulence e.g COVID-19	PDT
Operational uncertainty of energy stability and security	ESS
Operational uncertainty from generational work behaviour and ethics	GWB
Skills for future industrial work	SFW
Entrenchment power of large firms	EPL
Process capability and variations	PCV

Source: Author

Step 2: Design the fuzzy linguistic scale

The five-point scale was selected for the operational uncertainty assessment based on the level of its influence on manufacturing operations. The degree of influence is expressed using five linguistic terms and triangular fuzzy numbers.

Step 3: Generate a fuzzy matrix, measure the agreement and consistency of decision-makers and generate the mean fuzzy direct-relation matrix

The Kendall's W concordance degree scale with its corresponding Chi-square (χ^2) (Marcinkiewicz, 2017) for the dimensions is presented in Table 8.2. Based on the range by Moslem et al. (2019), the scale was mainly in strong agreement with $W > 0.6$ except for one in the moderate to strong agreement range ($0.3 < W < 0.6$). The highest level of agreement among decision-makers (high-level view) was for PCV, with $W = 0.850$, which indicates a high level of concordance. GPT follows this with $W = 0.789$, then PDT ($W = 0.782$), CLC ($W = 0.751$), and PRU ($W = 0.722$). The dimension with the lowest levels of concordance was GWB, with $W = 0.480$. This lowest level of concordance was still accepted as it was higher than $W = 0.3$.

Table 8.2: Kendall's W concordance for the dimensions

Dimensions	N	Kendall's W	χ^2	Df	p-value
GPT	22	0,789	138.9	8	0,000
PRU	22	0.722	127.1	8	0,000
CLC	22	0.751	132.2	8	0,000
PDT	22	0,782	137.6	8	0,000
ESS	22	0.688	121,1	8	0,000
GWB	22	0.480	84.52	8	0,000
SFW	22	0.613	108.0	8	0,000
EPL	22	0.629	110.6	8	0,000
PCV	22	0,850	149.6	8	0,000

Source: Author

The analysis was conducted with acceptable levels of agreement to evaluate individual-level consistency using the corrected Item-total correlation (Table 8.3).

Table 8.3: Corrected Item-total correlation

Experts	PCV	PRU	CLC	PDT	ESS	GWB	SFW	EPL	GPT
Expert 1	0.858	0.695	0.935	0.9757	0.539	0.739	0.595	0.800	0.758
Expert 2	0.814	0.875	0.890	0.7379	0.891	0.721	0.746	0.807	0.842
Expert 3	0.770	0.900	0.925	0.7699	0.863	0.644	0.670	0.899	0.858
Expert 4	0.770	0.766	0.950	0.7699	0.592	0.781	0.670	0.856	0.572
Expert 5	0.583	0.948	0.986	0.8482	0.958	0.773	0.548	0.947	0.816
Expert 6	0.852	0.952	0.939	0.9691	0.937	0.765	0.683	0.663	0.843
Expert 7	0.928	0.614	0.773	0.9838	0.772	0.835	0.361	0.886	0.658
Expert 8	0.903	0.795	0.966	0.9555	0.935	0.803	0.984	0.867	0.913
Expert 9	0.913	0.915	0.927	0.9845	0.903	0.529	0.793	0.854	0.818
Expert 10	0.961	0.808	0.856	0.9672	0.970	0.815	0.909	0.897	0.923
Expert 11	0.927	0.939	0.957	0.9227	0.971	0.739	0.764	0.911	0.867
Expert 12	0.956	0.920	0.927	0.9845	0.945	0.529	0.849	0.912	0.777
Expert 13	0.960	0.938	0.878	0.9532	0.961	0.835	0.679	0.894	0.920
Expert 14	0.962	0.939	0.979	0.9706	0.984	0.773	0.920	0.877	0.929
Expert 15	0.932	0.882	0.960	0.9905	0.980	0.603	0.797	0.817	0.878
Expert 16	0.903	0.943	0.947	0.9601	0.928	0.781	0.773	0.874	0.939
Expert 17	0.953	0.867	0.966	0.9905	0.961	0.803	0.985	0.865	0.956
Expert 18	0.924	0.962	0.927	0.9674	0.938	0.548	0.780	0.900	0.730
Expert 19	0.966	0.901	0.944	0.9874	0.932	0.690	0.925	0.861	0.956
Expert 20	0.961	0.915	0.947	0.9678	0.941	0.739	0.831	0.847	0.886
Expert 21	0.943	0.928	0.956	0.9719	0.947	0.723	0.888	0.928	0.931
Expert 22	0.935	0.952	0.982	0.9775	0.959	0.702	0.924	0.936	0.893

The results suggest excellent agreement among experts. The dimensions, PCV, EPL, CLC, and PRU show good agreement among the experts, with the lowest agreement being shown with GWB and SFW. Table 8.4 highlights the intraclass correlation. The intraclass correlation indicates the level of agreement or reliability among the experts' ratings for each construct (Shrout & Fleiss, 1979), based on the ICC interpretation of > 0.90 (Table 8.4).

Table 8.4: Intraclass correlation

	Intraclass Correlation	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
PCV	,989	0.975	0.997	87.987	8	168	0.000
PRU	,986	0.969	0.996	75.853	8	168	0.000
CLC	,993	0.984	0.998	150.999	8	168	0.000
PDT	,994	0.987	0.998	164.978	8	168	0.000
ESS	,989	0.974	0.997	96.168	8	168	0.000
GWB	,953	0.894	0.987	25.371	8	168	0.000
SFW	,969	0.931	0.992	36.365	8	168	0.000
EPL	,985	0.966	0.996	69.840	8	168	0.000
GPT	,979	0.952	0.994	55.950	8	168	0.000

Source: Author

The arithmetic mean was then developed from the experts' assessment to generate the direct relation matrix. This was based on all 22 experts, as they were all retained after Kendall's coefficient of concordance (W), Corrected item-total correlation, and intraclass correlation. The direct relation matrix generated is the same as the pairwise comparison matrix of the experts (Table 8.5).

Step 5: Normalise the fuzzy direct relation matrix;

Conversion from linear to normalised scale is conducted to obtain a compatible scale. The normalised fuzzy direct-relation matrix can then be determined (Table 8.6).

Table 8.5: Mean fuzzy direct-relation matrix

	GPT	PRU	CLC	PDT	ESS	GWB	SFW	EPL	PCV
GPT	(0.000,0.000,0.000)	(0.609,0.809,0.950)	(0.523,0.718,0.882)	(0.182,0.318,0.514)	(0.559,0.755,0.900)	(0.100,0.209,0.409)	(0.327,0.500,0.695)	(0.259,0.400,0.595)	(0.077,0.182,0.382)
PRU	(0.486,0.673,0.859)	(0.000,0.000,0.000)	(0.268,0.436,0.636)	(0.255,0.409,0.609)	(0.223,0.345,0.545)	(0.305,0.491,0.691)	(0.409,0.609,0.800)	(0.423,0.618,0.805)	(0.145,0.264,0.464)
CLC	(0.300,0.473,0.668)	(0.359,0.555,0.755)	(0.000,0.000,0.000)	(0.355,0.527,0.718)	(0.327,0.527,0.727)	(0.564,0.764,0.932)	(0.600,0.800,0.950)	(0.545,0.745,0.914)	(0.655,0.855,0.977)
PDT	(0.159,0.264,0.464)	(0.509,0.700,0.882)	(0.500,0.700,0.895)	(0.000,0.000,0.000)	(0.068,0.182,0.382)	(0.536,0.736,0.909)	(0.482,0.682,0.877)	(0.491,0.691,0.886)	(0.609,0.809,0.950)
ESS	(0.418,0.618,0.805)	(0.536,0.727,0.882)	(0.518,0.718,0.905)	(0.018,0.118,0.318)	(0.000,0.000,0.000)	(0.445,0.627,0.809)	(0.445,0.636,0.832)	(0.345,0.536,0.736)	(0.564,0.764,0.927)
GWB	(0.159,0.291,0.491)	(0.400,0.582,0.777)	(0.282,0.445,0.645)	(0.214,0.373,0.573)	(0.241,0.409,0.609)	(0.000,0.000,0.000)	(0.482,0.664,0.832)	(0.250,0.400,0.600)	(0.259,0.409,0.605)
SFW	(0.159,0.282,0.482)	(0.173,0.309,0.509)	(0.414,0.600,0.791)	(0.273,0.427,0.627)	(0.364,0.536,0.718)	(0.477,0.673,0.859)	(0.000,0.000,0.000)	(0.164,0.282,0.482)	(0.432,0.618,0.809)
EPL	(0.268,0.418,0.618)	(0.355,0.527,0.727)	(0.505,0.700,0.882)	(0.164,0.300,0.500)	(0.459,0.655,0.841)	(0.441,0.636,0.818)	(0.455,0.655,0.841)	(0.000,0.000,0.000)	(0.436,0.636,0.832)
PCV	(0.036,0.136,0.336)	(0.059,0.164,0.364)	(0.395,0.591,0.791)	(0.095,0.209,0.409)	(0.377,0.555,0.736)	(0.105,0.209,0.409)	(0.418,0.609,0.809)	(0.541,0.736,0.900)	(0.000,0.000,0.000)

Table 8.6: The normalized fuzzy direct-relation matrix

	GPT	PRU	CLC	PDT	ESS	GWB	SFW	EPL	PCV	
GPT	(0.000,0.000,0.000)	(0.092,0.122,0.143)	(0.079,0.108,0.133)	(0.027,0.048,0.077)	(0.084,0.114,0.136)	(0.015,0.031,0.062)	(0.049,0.075,0.105)	(0.039,0.060,0.090)	(0.012,0.027,0.058)	
PRU	(0.073,0.101,0.129)	(0.000,0.000,0.000)	(0.040,0.066,0.096)	(0.038,0.062,0.092)	(0.034,0.052,0.082)	(0.046,0.074,0.104)	(0.062,0.092,0.120)	(0.064,0.093,0.121)	(0.022,0.040,0.070)	
CLC	(0.045,0.071,0.101)	(0.054,0.084,0.114)	(0.000,0.000,0.000)	(0.053,0.079,0.108)	(0.049,0.079,0.109)	(0.085,0.115,0.140)	(0.090,0.120,0.143)	(0.082,0.112,0.138)	(0.099,0.129,0.147)	
PDT	(0.024,0.040,0.070)	(0.077,0.105,0.133)	(0.075,0.105,0.135)	(0.000,0.000,0.000)	(0.010,0.027,0.058)	(0.081,0.111,0.137)	(0.073,0.103,0.132)	(0.074,0.104,0.133)	(0.092,0.122,0.143)	
ESS	(0.063,0.093,0.121)	(0.081,0.109,0.133)	(0.078,0.108,0.136)	(0.003,0.018,0.048)	(0.000,0.000,0.000)	(0.067,0.094,0.122)	(0.067,0.096,0.125)	(0.052,0.081,0.111)	(0.085,0.115,0.140)	
GWB	(0.024,0.044,0.074)	(0.060,0.088,0.117)	(0.042,0.067,0.097)	(0.032,0.056,0.086)	(0.036,0.062,0.092)	(0.000,0.000,0.000)	(0.073,0.100,0.125)	(0.038,0.060,0.090)	(0.039,0.062,0.091)	
SFW	(0.024,0.042,0.073)	(0.026,0.047,0.077)	(0.062,0.090,0.119)	(0.041,0.064,0.094)	(0.055,0.081,0.108)	(0.072,0.101,0.129)	(0.000,0.000,0.000)	(0.025,0.042,0.073)	(0.065,0.093,0.122)	
EPL	(0.040,0.063,0.093)	(0.053,0.079,0.109)	(0.076,0.105,0.133)	(0.025,0.045,0.075)	(0.069,0.099,0.127)	(0.066,0.096,0.123)	(0.069,0.099,0.127)	(0.000,0.000,0.000)	(0.066,0.096,0.125)	
PCV	(0.005,0.020,0.051)	(0.009,0.025,0.055)	(0.059,0.089,0.119)	(0.014,0.031,0.062)	(0.057,0.084,0.111)	(0.016,0.031,0.062)	(0.063,0.092,0.122)	(0.081,0.111,0.136)	(0.000,0.000,0.000)	

Step 6: Determine fuzzy total-relation matrix

The fuzzy total-relation matrix was determined in this system. The fuzzy total-relation matrix was critical in identifying and quantifying the causal relationships among factors in this complex system.

Step 7: Causal analysis.

Causal relation analysis to determine the most important factor and how it is classified to understand the cause and effect. Table 8.7 shows the final output.

Table 8.7: Output of the fuzzy-DEMATEL model

	R	D	D+R	D-R
GPT	1,878	2,245	4,123	0,367
PRU	2,366	2,21	4,576	-0,157
CLC	2,647	2,743	5,39	0,096
PDT	1,677	2,564	4,241	0,886
ESS	2,262	2,55	4,812	0,288
GWB	2,427	2,082	4,509	-0,345
SFW	2,783	2,152	4,935	-0,631
EPL	2,441	2,488	4,929	0,047
PCV	2,5	1,949	4,45	-0,551

Figure 8.1 shows the model of significant relations focusing on the causes and effects. This model can be represented as a diagram in which the values of (D+R) are placed on the horizontal axis and the values of (D-R) on the vertical axis.

The coordinate system determines the position and interaction of each factor with a point in the coordinates (D+ R, D-R). The horizontal vector (D + R) represents the degree of importance each dimension plays in the entire system. In other words, (D + R) indicates both factor i's impact on the whole system and other system factors' impact on the factor. Regarding the degree of importance, CLC is ranked first, and SFW, EPL, ESS, PRU, GWB, PCV, PDT, and GPT are ranked next. In this study, GPT, CLC, PDT, ESS, and EPL are considered causal variables, and PRU, GWB, SFW, and PCV are regarded as effects

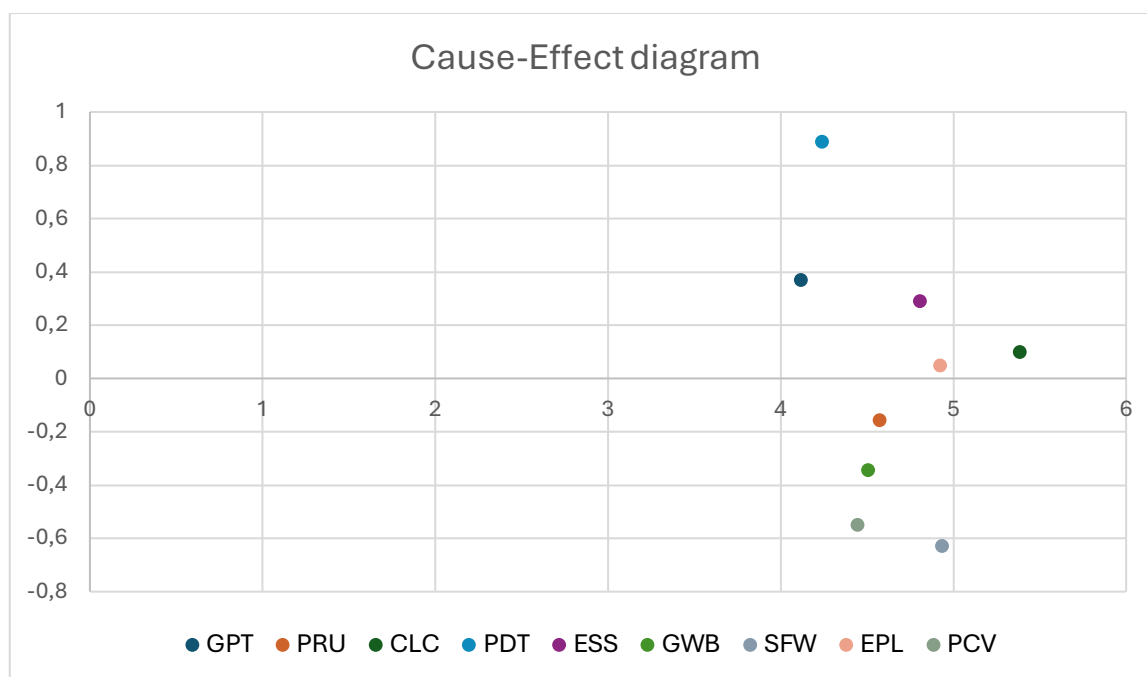


Figure 8.1: Cause-effect diagram

8.3 Build fsQCA conditions for configurations

Fiss (2007), and later supported by Woodside et al. (2018), posited that configurations can emerge conceptually or empirically; both are designed to characterise "what" configurations exist in the area of interest. In the present study, the configurations were built based on the model explained in **Chapter 4 (section 4.6.4.3) - Figure 4.2 Configurations of the study**. Table 8.8 provides information on the conditions for building the configurations. The causal conditions were operational uncertainty (X) dimensions were classified as causal in Fuzzy-DEMATEL, Industry 4.0 and Industry 5.0 technologies and their capabilities (W), organisational learning (Z) and outcome being sustained performance (Y). These were all validated in the earlier chapters. The approach in the building was that the model must have more than one but not more than seven causal conditions. This is in line with the recommendations of Fainshmidt et al. (2020, p.457), who argued that "models with more than seven causal conditions can be constructed in principle, but given the large number of parameters involved, the results can become difficult to interpret, and such models should therefore be avoided" At the same time these authors explained that single causal condition is rarely sufficient to explain the presence of a particular outcome.

Table 8.8: Conditions for fsQCA analysis

Causal condition Operational uncertainty (X) Validation method: Fuzzy-DEMATEL	Causal condition Industry 4.0 and 5.0 technologies (W) Validation method: Heatmap, PLS-SEM measurement model	Causal condition Organisational learning (Z) Validation method: Corrected Item-total correlation, Pearson correlation	Outcome (Y) Sustained performance Validation method: PLS-SEM measurement model
Model I: Growing political tensions (GPT)	Scenario planning and supply chain integration (SPSI)** Flexible production and mass customization (FPMC) Real-time system and process monitoring and response (RPMR) IoT, AI, ARB, BCC	Organisational learning (OLN)	Sustained performance (SPF)
Model II: Cost of living-driven consumer behavioural change (CLC)	Scenario planning and supply chain integration (SPSI) Flexible production and mass customization (FPMC) IoT, AI, BCC, ARB, BDA*		
Model III: Pandemic turbulence (PDT)	Scenario planning and supply chain integration (SPSI) Flexible production and mass customisation (FPMC) Real-time system and process monitoring and response (RPMR) Protective ecosystem (human and system) (PEHS) IoT, AI, BCC, ARB, BDA*, ARVR, QCP		
Model IV: Operational uncertainty of energy stability and security (ESS)	Real-time system and process monitoring and response (RPMR) Scenario planning and supply chain integration (SPSI) Root cause analysis and sustainable solutions (RCAS) IoT, AI, ARB, BDA*, ARVR		
Model V: Entrenchment power of large firms (EPL)	Scenario planning and supply chain integration (SPSI) IoT, AI, BCC, ARB		

**SPSI – developed from integration of SPFP and SCIC due to discriminant lack of validity

Source: Author

8.4 Structural models – Direct effect of causal model

The structural model with the five casual conditions used are presented in Figure 8.2. The model was analysed, and showed good model fit using SRMR = 0.078. This was a good fit as it was better than both the conservative value of 0.080 (Hu & Bentler, 1998) and the recommended threshold of 0.10 (Henseler et al., 2014). The model had good reliability and validity with all values for reliability >0.7 and AVE for convergence validity ≥ 0.50 and discriminant validity using HTMT less than $H_{.85}$.

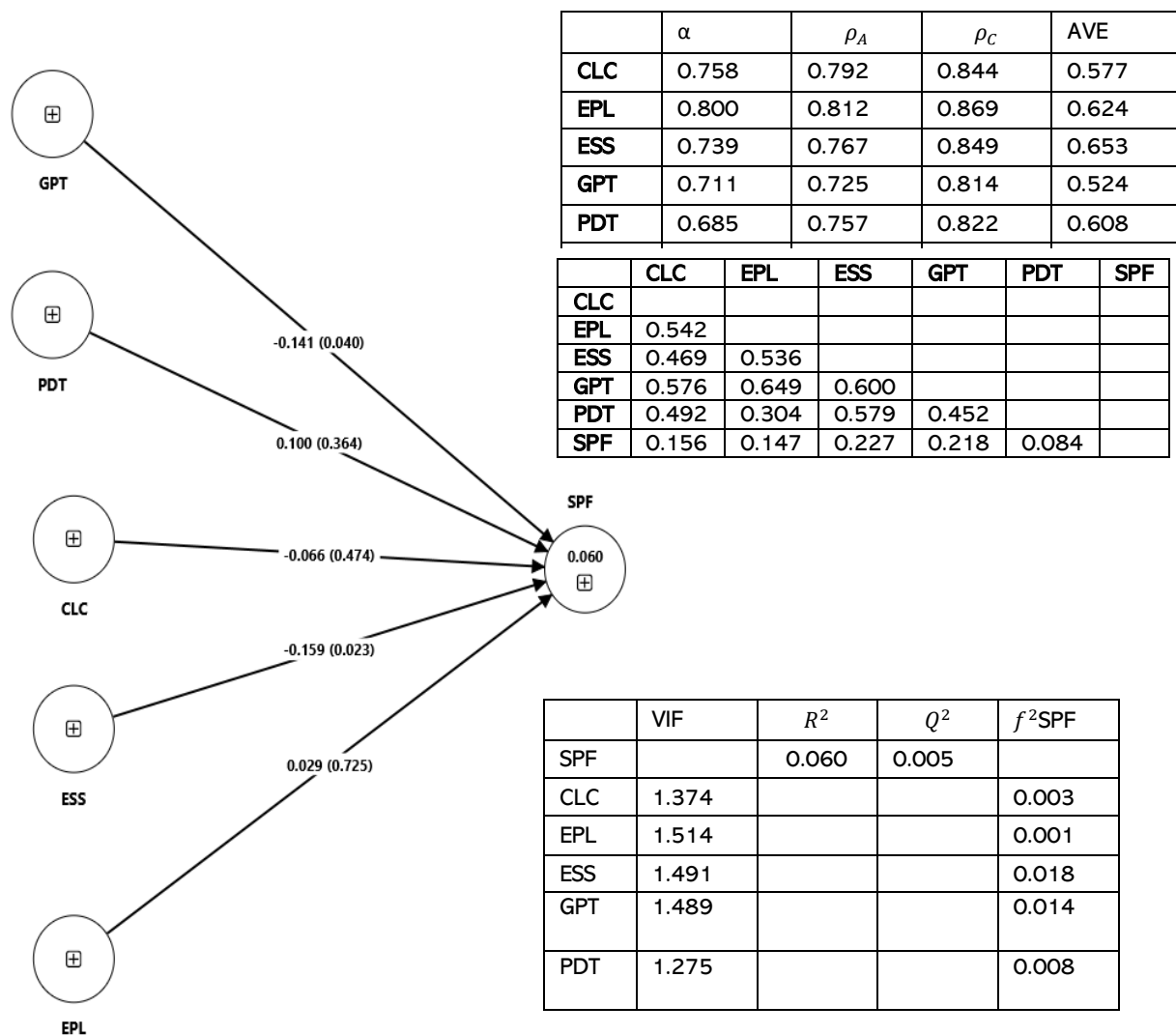


Figure 8.2: Structural model of the causal conditions with outcome, SPF

Source: Author

The model had acceptable explanatory and predictive power (Shmueli et al., 2019). This was important as the model's validity and utility would be compromised if it did not have such abilities. The model had an acceptable predictive power with Stone-Geisser $Q^2 > 0$. Though the model had a lower $R^2 = 0.060$, it was deemed acceptable as the model demonstrates acceptable predictive relevance (Q^2) (Suhan & Achar, 2016) as well as model performance with acceptable SRMR (Yusif et al., 2020). The path coefficients for the structural model shows that GPT has a statistically significant negative relationship with SPF ($\beta = -0.141$, $p < .05$). There was also a statistically negative relationship between ESS and SPF ($\beta = -0.159$, $p < .05$). The other three paths were not statistically significant. As such, the main focus of the fsQCA was on the two significant paths and the overall model validated earlier as a higher-order constructs.

8.5 Measurement and structural models

8.5.1 Geopolitical tension-based model (Model I)

The measurement and structural analysis of the model I was analysed, which was important for the conditions of the fsQCA. This is because the fsQCA cannot analyse the model for reliability and validity. The model's analysis used the causal operational uncertainty dimensions—geopolitical tension, organisational learning, and Industry 4.0 and 5.0 technologies with capabilities and sustained performance (outcome condition). The measurement confirmed reliability, with Cronbach alpha and composite reliability ≥ 0.60 (Table 8.9).

Table 8.9: Reliability and convergence validity for Model I

	Cronbach's alpha	Composite reliability (ρ_A)	Composite reliability (ρ_c)	Average variance extracted (AVE)
FPMC	0.621	0.958	0.819	0.698
GPT	0.711	0.718	0.807	0.514
OLN	0.763	0.771	0.838	0.508
RPMR	0.646	0.673	0.811	0.594
SPF	0.790	0.849	0.874	0.699
SPSI	0.793	0.816	0.857	0.602

Source: Author

The measurement model also confirmed the discriminant validity for Model I, with HTMT less than $H_{.85}$ (Table 8.10).

Table 8.10: Discriminant validity with HTMT for Model I

	AI	BCC	FPMC	GPT	OLN	RPMR	SPF	SPSI
AI								
BCC	0.055							
FPMC	0.081	0.131						
GPT	0.286	0.079	0.139					
OLN	0.169	0.096	0.283	0.115				
RPMR	0.079	0.156	0.676	0.180	0.274			
SPF	0.064	0.089	0.107	0.181	0.185	0.143		
SPSI	0.041	0.082	0.649	0.090	0.326	0.522	0.242	

Source: Author

The model had no issues with multicollinearity with variance inflation factor (VIF) values less than 5.0 (Hair et al., 2019) and Kock's proposed threshold of 3.3 (Kock, 2015) for observed common method bias. The model also had good explanatory and predictive power with $R^2 = 0.095$ and Stone-Geisser $Q^2 > 0$ (Chin, 1998; Suhan & Achar, 2016). The f^2 is effect size, which indicates that different dimensions may influence the variable in a structural model. Based on the guidelines of Cohen (1988), in this model, the effect size was small (≥ 0.02) to medium (≥ 0.15) for GPT ($f^2 = 0.032$) and SPSI ($f^2 = 0.043$) while the others were negligible (Table 8.11).

Table 8.11: Explanatory and predictive power for Model I

	VIF	R^2	Q^2	f^2_{SPF}
SPF		0.095	0.006	
AI	1.096			0.000
BCC	1.035			0.005
FPMC	1.347			0.002
GPT	1.080			0.032
OLN	1.140			0.008
RPMR	1.309			0.000
SPF	1.353			0.043

Source: Author

Table 8.12 presents the paths for geopolitical tension-based model. The model shows a statistically significant negative relationship between the GPT and SPF ($\beta = -0.187$, $p \leq .05$). There is a statistically significant positive relationship in the SPSI $\rightarrow$ SPF ($\beta = 0.226$, $p < .01$). The other paths were not statistically significant with a p-value more than 5%

Table 8.12: Path coefficient of Model I

	β	T statistics	p-values
AI $\rightarrow$ SPF	0.036	0.263	0.792
BCC $\rightarrow$ SPF	0.196	1.006	0.314
FPMC $\rightarrow$ SPF	-0.042	0.555	0.579
GPT $\rightarrow$ SPF	-0.187	2.523	0.012
OLN $\rightarrow$ SPF	0.106	1.224	0.221
RPMR $\rightarrow$ SPF	0.014	0.140	0.888
SPSI $\rightarrow$ SPF	0.226	3.289	0.001

8.5.2 Energy stability and security-based model (Model IV)

Table 8.13 provides the reliability and convergence validity of the energy stability and security-based model (model IV). This model is reliable with all values ≥ 0.60 with the values for $\alpha = 0.646 - 0.800$, while those for $\rho_A = 0.693 - 0.894$ and $\rho_c = 0.810 - 0.857$. The convergence validity was also good with $AVE \geq 0.50$, ranging from 0.531 – 0.751.

Table 8.13: Reliability and convergence validity for Model IV

	Cronbach's alpha	Composite reliability (ρ_A)	Composite reliability (ρ_c)	Average variance extracted (AVE)
ESS	0.739	0.761	0.851	0.656
OLN	0.800	0.894	0.849	0.532
RCAS	0.693	0.878	0.857	0.751
RPMR	0.646	0.693	0.810	0.594
SPF	0.790	0.834	0.875	0.702
SPSI	0.793	0.814	0.857	0.601

Note: IMT16 from RCAS and IMT from RPMR excluded due to low factor loadings

The model had good discriminant validity with HTMT values less than $H_{.85}$ (Table 8.14).

Table 8.14: Discriminant validity with HTMT for Model IV

	AI	BDA	ESS	OLN	RCAS	RPMR	SPF	SPSI
AI								
BDA	0.088							
ESS	0.282	0.114						
OLN	0.130	0.096	0.112					
RCAS	0.140	0.066	0.054	0.421				
RPMR	0.079	0.054	0.109	0.278	0.763			
SPF	0.064	0.036	0.232	0.201	0.159	0.143		
SPSI	0.041	0.045	0.087	0.403	0.554	0.522	0.242	

Source: Author

Model IV also had no issues with multicollinearity with VIF ranging from values 1.031 – 1.475. Similar to Model I, these values were less than the threshold of 5.0 (Hair et al., 2019) and Kock's proposed threshold of 3.3 (Kock, 2015) for observed common method bias. The model also had good explanatory and predictive power with $R^2 = 0.095$ and the Stone-Geisser $Q^2 > 0.025$ ($Q^2 > 0$, Chin, 1998). The f^2 in this model was small (≥ 0.02) to medium (≥ 0.15) for ESS ($f^2 = 0.042$) and SPSI ($f^2 = 0.025$) (Table 8.15).

Table 8.15: Explanatory and predictive power for model IV

	VIF	R^2	Q^2	f^2_{SPF}
SPF		0.103	0.025	
AI	1.093			0.000
BDA	1.031			0.002
ESS	1.073			0.042
OLN	1.197			0.019
RCAS	1.475			0.001
RPMR	1.377			0.001
SPSI	1.344			0.025

Source: Author

These results show a statistically significant negative relationships in the paths ESS -> SPF ($\beta = -0.209$, $p < .01$) and a positive relationship in the path, SPSI -> SPF ($\beta = 0.174$, $p < .01$) (Table 8.16)

Table 8.16: Path coefficient of Model IV

	β	T statistics	P values
AI -> SPF	0.022	0.127	0.899
BDA -> SPF	-0.100	0.752	0.452
ESS -> SPF	-0.209	3.280	0.001
OLN -> SPF	0.152	1.619	0.105
RCAS -> SPF	0.023	0.481	0.631
RPMR -> SPF	-0.003	0.500	0.617
SPSI -> SPF	0.174	2.811	0.005

Source: Author

8.5.3 Operation uncertainty causal multidimension

The model for casual multidimensional construct, operational uncertainty was based on the higher-order construct with casual dimensions – GPT, PDT, CLC, ESS and EPL. The model fit, SRMR = 0.071 and reliability of the model was confirmed with $\alpha = 0.763$ – 0.845, while those for $\rho_A = 0.792$ – 0.905 and $\rho_c = 0.832$ – 0.905 (Table 8.17).

Table 8.17: Reliability and convergence validity of Model VI

	Cronbach's alpha	Composite reliability (ρ_A)	Composite reliability (ρ_c)	Average variance extracted (AVE)
OLN	0.763	0.788	0.836	0.505
OPU2	0.765	0.794	0.832	0.504
PEHS	0.771	0.792	0.857	0.667
SPF	0.845	0.867	0.905	0.761
SPSI	0.793	0.845	0.853	0.594

SRMR = 0.071

Source: Author

The discriminant validity was confirmed with the HTMT with all values below the threshold of 0.85 ($H_{.85}$) (Table 8.18).

Table 8.18: Discriminant validity with HTMT of Model VI

	AI	ARVR	BDA	OLN	OPU2	PEHS	SPF	SPSI
AI								
ARVR	0.151							
BDA	0.088	0.146						
OLN	0.169	0.077	0.072					
OPU 2	0.275	0.101	0.167	0.150				
PEHS	0.099	0.093	0.045	0.398	0.089			
SPF	0.065	0.042	0.042	0.194	0.225	0.142		
SPSI	0.041	0.058	0.045	0.326	0.101	0.362	0.202	

Model VI also had no issues with multicollinearity with VIF = 1.056 – 1.177. Similar to both Model I and Model IV these values were less than 5.0 (Hair et al., 2019) and 3.3 for observed common method bias (Kock, 2015). The model also had good explanatory and predictive power with $R^2 = 0.100$ and the Stone-Geisser $Q^2 > 0$ (Chin, 1998) (Table 8.19). The f^2 in this model was small (≥ 0.02) to medium (≥ 0.15) for OPU2 ($f^2 = 0.051$) and SPSI ($f^2 = 0.025$).

Table 8.19: Explanatory and predictive power for Model VI

	VIF	R^2	Q^2	f^2_{SPF}
SPF		0.100		
AI	1.118			0.002
ARVR	1.065			0.000
BDA	1.056			0.001
OLN	1.177			0.014
OPU 2	1.097			0.051
PEHS	1.192			0.001
SPSI	1.153			0.025

The model VI shows a statistically significant negative relationship between the OPU2 and SPF ($\beta = -0.244$, $p \leq .001$) and a positive relationship for SPSI and SPF ($\beta = 0.168$,

$p < .01$) (Table 8.20). The other paths were not statistically significant with p -value more than 5%

Table 8.20: Path coefficient of Model VI

	β	T statistics	P values
AI -> SPF	0.087	0.630	0.529
ARVR -> SPF	-0.006	0.137	0.891
BDA -> SPF	-0.080	0.596	0.551
OLN -> SPF	0.136	1.868	0.062
OPU2 -> SPF	-0.244	3.707	0.000
PEHS -> SPF	0.041	0.421	0.674
SPSI -> SPF	0.168	2.666	0.008

Source: Author

8.6 FsQCA – solutions

There are two schools of thought on the input of the conditions to the fsQCA. The one is the use of the standardised latent scores from the PLS-SEM (Rasoolimanesh et al., 2021; Sukhov et al., 2023), while the other is the use of the means of multi-indicator dimensions or constructs (Papas & Woodside, 2021). Papas and Woodside (2021, p. 8) explained, “When a variable or construct is measured with multiple items, we need to compute one value per construct that will be used as input in fsQCA.”

8.6.1 Geopolitical tension

Latent variable score-based fsQCA solutions were conducted for the conditions in the presence of the geopolitical tension. The analysis and the solution was based on the model based on the Quine-McCluskey algorithm. The causal conditions were GPT, OLN, SPSI, FPMC, RPMC, AI, BCC, while the outcome is SPF (1 indicates presence of the outcome, 0 indicates absence). The unique latent variable (LV) scores developed from PLS-SEM were used and calibrated based on the percentile approach proposed by Rasoolimanesh et al. (2021). This percentile uses 3 = full membership, 0 = cross over, and -3 for non-membership, where the full membership represents 99.9% percentile while -3 is 0.1% percentile (Rasoolimanesh et al., 2021). The truth table is analysed using logical minimisation to identify the sufficient and necessary conditions (Schneider &

Wagemann, 2012). Each row in the truth table represents the unique configuration of the conditions (Table 8.21).

Table 8.21: Truth table with an allotment of solution scores

GPT	OLN	SPSI	FPMC	RPMR	AI	BCC	number	SPF	raw consist,	PRI consist,	SYM consist
0	1	1	1	1	0	1	6	1	1,000	1,000	1,000
0	0	0	1	0	1	0	3	1	0,955	0,574	0,574
0	1	1	0	0	1	0	4	1	0,951	0,567	0,567
1	1	0	1	0	1	0	4	1	0,948	0,535	0,539
1	0	1	1	0	1	0	4	1	0,946	0,519	0,519
0	1	0	0	0	1	0	5	1	0,946	0,533	0,535
0	0	0	1	1	1	0	3	1	0,943	0,462	0,462
1	1	1	1	0	1	0	7	1	0,940	0,489	0,490
0	0	1	0	1	1	0	3	1	0,938	0,462	0,462
0	1	0	1	1	1	0	6	1	0,938	0,467	0,469
0	1	1	0	1	1	0	4	1	0,937	0,500	0,501
1	0	1	1	1	1	0	5	1	0,937	0,483	0,486
1	0	0	0	1	1	0	3	1	0,936	0,450	0,455
0	1	0	0	1	1	0	4	1	0,936	0,452	0,452
1	1	0	1	1	1	0	6	1	0,933	0,475	0,475
0	0	1	1	1	1	0	4	1	0,933	0,431	0,434
1	0	1	0	0	1	0	4	1	0,933	0,448	0,451
0	0	0	0	0	1	0	8	1	0,931	0,399	0,403
1	1	1	0	1	1	0	4	1	0,928	0,469	0,469
0	1	1	1	1	1	0	20	1	0,925	0,554	0,564
1	1	0	0	0	1	0	9	1	0,925	0,478	0,494
0	1	1	1	1	0	0	9	1	0,916	0,686	0,691
1	1	1	0	0	1	0	9	1	0,913	0,416	0,428
1	0	0	0	0	1	0	8	1	0,909	0,375	0,376
1	1	1	1	1	1	0	18	1	0,900	0,434	0,449
1	1	1	1	1	0	0	5	1	0,896	0,497	0,510
0	1	1	1	0	0	0	3	1	0,892	0,390	0,390
0	1	0	0	0	1	1	4	1	0,856	0,464	0,469
0	0	1	1	1	0	0	8	1	0,852	0,459	0,470
0	0	0	0	0	0	0	4	1	0,850	0,398	0,420
1	1	0	0	0	1	1	3	0	0,812	0,223	0,223
1	0	0	1	0	0	0	3	0	0,800	0,214	0,214

Source: Author

The raw consistency measures the consistency of a configuration that leads to an outcome. The proportional reduction in inconsistency (PRI) also measures how consistent a configuration is in uniquely explaining the outcome, excluding the contradictory cases,

while the symmetry reflects the symmetry of consistency between the outcome and the absence of the outcome. A total of 32 alternatives were produced from the truth table after removing the alternatives with less than three cases (cutoff = 3) and Table 8.22 reports the allotment of solution scores '0' and '1' from this truth table.

A standard analysis was conducted which included the causal combinations to achieve sustainable performance during growing geopolitical tension with acceptable consistency >0.80 and coverage (>0.20) (Ragin, 2008a). The minimum expected value is crucial in ensuring that the identified conditions are statistically significant and theoretically meaningful, providing a robust framework for causal inference in fsQCA. A threshold of ≥ 0.75 (Mejía-Trejo, 2023) was used as the guide for consistency also noting and there is also a more stringent guide of > 0.80 from other authors such as Ragin (2008a), with a coverage greater than 0.2. This was considered sufficient to generate the outcome,

Fiss (2011), and later supported by Papas and Woodside (2021), suggested a combined use of intermediate and parsimonious results to identify the core and peripheral conditions. Papas and Woodside (2021, p.12) explained, "the intermediate solution presents both core and peripheral conditions, and peripheral conditions are removed from the parsimonious solution, an easy way to identify the core conditions is to examine the parsimonious solution." In examining parsimonious solutions, the conditions; SPSI and $\sim$ cGPT were present in both solutions and have high consistency and coverage, indicating them as the core conditions, while the others are peripheral conditions. These core causal conditions are strongly linked to the outcome leveraging both the present or absent conditions (Ragin, 2008a).

The analysis produced 12 solutions for high sustained performance (SPF). In Table 8.21, the presence of the condition is denoted by a black circle, while the absence is denoted by an empty circle, while the blank space denoted 'do not care' are based on the guide by Fiss (2011). The large circle denotes the core condition while the small circle represents the peripheral condition.

Table 8.22: Sufficient configurations of high sustained performance in the presence of geopolitical tension and industry 4.0 and 5.0 technologies capabilities and organisational learning

	Solution											
Configuration	1	2	3	4	5	6	7	8	9	10	11	12
GPT	●	○		○	○		●	●	○	●	○	○
OLN			●	●	●	●	●		○	○	●	○
SPSI		●	●		●	●		●	○		○	○
FPMC	○	●	○				●	●	○	○	○	●
RPMR	○	●		●	●	●			○		○	
AI	●		●	●	●	●	●	●		●	●	●
BCC	○	○	○	○	○	○	○	○	○	○		○
Raw coverage	0.388	0.499	0.377	0.371	0.381	0.519	0.383	0.393	0.453	0.355	0.376	0.327
Unique coverage	0.011	0.008	0.004	0.003	0.002	0.010	0.007	0.008	0.027	0.005	0.056	0.004
Consistency	0.869	0.899	0.886	0.895	0.899	0.887	0.874	0.870	0.906	0.895	0.933	0.936

Overall solution coverage 0.832

Solution consistency 0.799

High SPF: PSPF = f(GPT, OLN, SPSI, FPMC, RPMR, AI, BCC)

Note: Black circles indicate the presence of conditions, and empty circles indicate the absence of condition

Large circle: core condition small circle: peripheral condition blank space: "don't care condition"

Parsimonious solution (Core conditions): SPSI (coverage – 0.802, consistency – 0.793), ~GPT (coverage – 0.777, consistency – 0.783)

Necessary conditions: SPSI: consistency – 0.802, coverage 0.793

The solution coverage and consistency were good. The solution coverage indicated how well the combination of the conditions explain the outcome. In these results it was 0.832 implying that the solution covers about 83.2% of the cases. The solution consistency accounts for how well the combination of conditions consistently predicts the outcome which in this case was 0.799, implying a consistency of 79.9%. Within these 12 solutions, four had the presence of geopolitical tension (GPT), and this is the main focus as it is assumed to be present in the firm. These are solutions 1, 7, 8 and 10. To achieve sustained performance in the presence of GPT, it may be combined with solution 1 (AI in the absence of FPMC, RPMC and BCC) or solution 7 (OLN, FPMC and AI), solution 8 (SPSI, FPMC, AI in absence of BCC) and solution 10 (AI in the absence of OLN, FPMC and BCC). There are six solutions that show the achievement of high sustained performance in the absence of GPT. A necessary condition analysis was conducted for these solutions. Rihoux and Ragin (2009) posited that the necessary condition is regarded as the superset of the outcome.

Conditions with consistency and coverage >0.9 are regarded as necessary conditions. In this analysis, the SPSI had strong consistency – 0.802, coverage 0.793 appeared to be a candidate for explaining the variations in high SFP. This is despite it not reaching > 0.9 . Despite this, in the strictest term these solutions have no necessary condition (Ragin, 2009). Four specific sub-propositions were tested based on solutions 1, 7, 8, and 10 regarding the achievement of high sustained performance in the presence of geopolitical tension when managed with the Industry 4.0 and 5.0 technologies capabilities. Solution 1 and 10 are the same for the presence of GPT and AI. The other three sub-propositions are provided in Figure 8.3. The X-axis typically represents the degree of membership in a causal condition, while the Y-axis represents the degree of membership in the outcome (Mejía Trejo, 2023). Consistency measures the degree to which cases with a high membership in the condition also have a high membership in the outcome, and coverage assesses the extent to which the condition accounts for the outcome (Cangialosi, 2023). In looking at the presence of operational uncertainty in combination with organisational learning and Industry 4.0 and 5.0 technologies and capabilities.

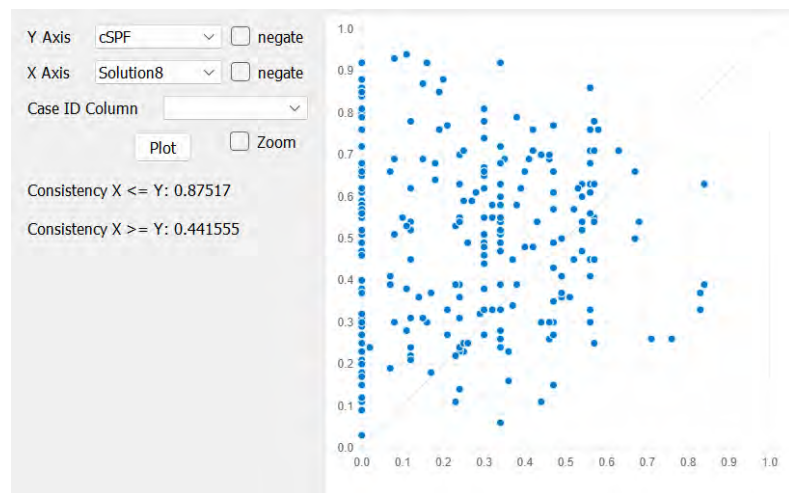
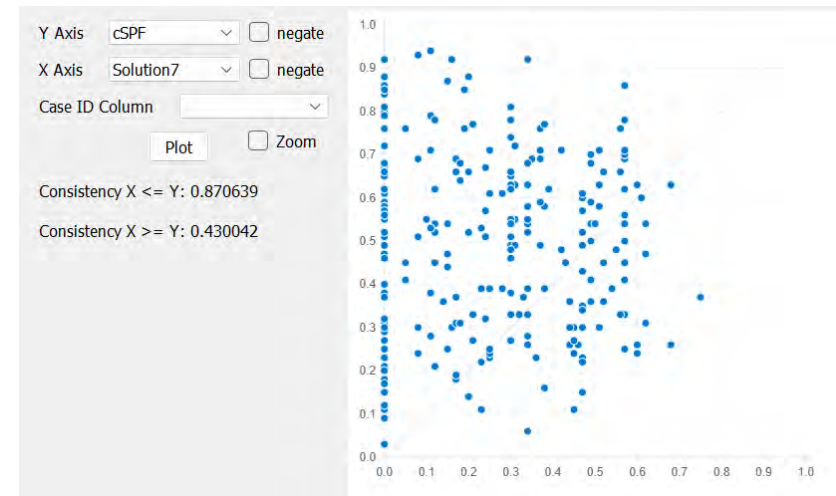
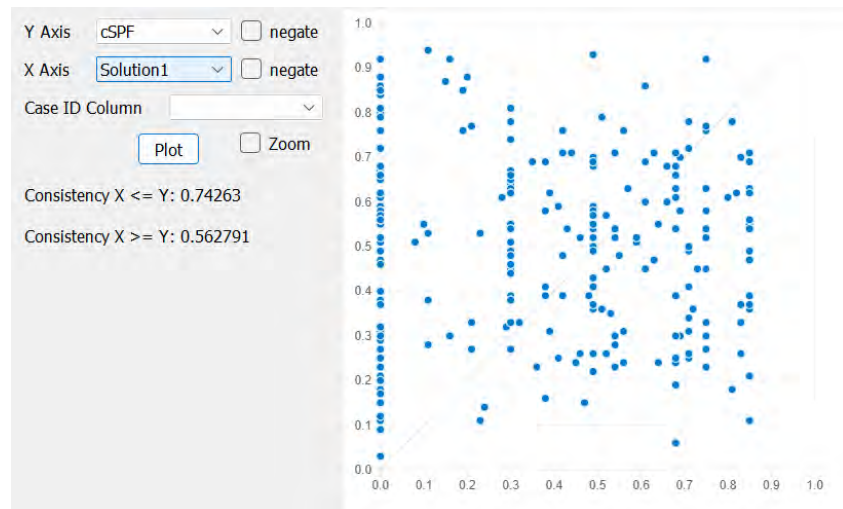


Figure 8.3: XY Plots of fsQCA for solutions in the presence of GPT

With high $X \leq Y$ for solution 8, (0.876) and solution 7 (0.871), and moderate to low $X \geq Y$, this indicates that the proposition is partially supported and that the solution with high performance depends on a large group of firms. However, it does not predict all the cases. The same applies to solution 1.

8.6.2 Energy stability and security

Table 8.23 provides the allotment of solution scores (truth table) and Table 8.24 the solutions for sufficient configurations of high sustained performance.

Table 8.23: Truth table with allotment of solution scores

ESS	OLN	RCAS	RPMR	SPSI	AI	BDA	number	SPF	Raw consist.	PRI consist.	SYM consist
0	0	0	1	1	1	0	4	1	0.972	0.746	0.750
1	0	1	1	1	1	0	4	1	0.964	0.739	0.756
0	1	1	1	1	1	0	3	1	0.963	0.642	0.649
0	0	1	1	0	1	0	3	1	0.961	0.660	0.660
1	1	1	0	0	1	0	5	1	0.956	0.659	0.659
1	0	1	1	0	1	0	3	1	0.953	0.611	0.614
1	1	1	1	1	1	0	5	1	0.952	0.629	0.629
1	1	0	0	1	1	0	3	1	0.950	0.665	0.665
0	0	1	1	1	1	0	3	1	0.949	0.558	0.558
1	0	0	0	1	1	1	5	1	0.947	0.530	0.530
0	1	0	0	0	1	1	4	1	0.947	0.607	0.616
0	0	0	0	1	1	1	4	1	0.940	0.463	0.475
1	1	0	0	0	1	1	4	1	0.940	0.504	0.504
1	1	0	0	1	1	1	3	1	0.939	0.498	0.498
1	1	0	1	0	1	0	3	1	0.937	0.524	0.524
0	1	0	1	1	1	1	3	1	0.937	0.492	0.493
1	1	1	1	1	0	1	6	1	0.931	0.684	0.710
0	1	0	1	1	0	1	3	1	0.931	0.709	0.709
1	0	1	0	1	1	0	5	1	0.930	0.472	0.478
0	1	1	0	0	1	1	3	1	0.927	0.457	0.457
0	1	1	1	1	1	1	8	1	0.925	0.591	0.592
1	0	0	0	0	1	0	3	1	0.924	0.438	0.438
0	1	1	1	1	0	1	9	1	0.922	0.755	0.755
1	0	1	0	0	1	1	4	1	0.921	0.439	0.439
0	0	0	0	0	1	1	6	1	0.921	0.440	0.440
0	1	1	0	1	1	1	3	1	0.921	0.452	0.452
0	0	1	1	1	1	1	7	1	0.920	0.427	0.430
1	1	1	0	0	1	1	5	1	0.920	0.433	0.442
1	1	1	0	1	1	1	5	1	0.915	0.415	0.416

ESS	OLN	RCAS	RPMR	SPSI	AI	BDA	number	SPF	Raw consist.	PRI consist.	SYM consist
1	1	1	1	1	0	0	3	1	0.913	0.612	0.664
1	0	1	1	1	1	1	5	1	0.911	0.322	0.331
1	0	1	1	0	1	1	3	1	0.908	0.338	0.343
1	0	0	0	0	1	1	7	1	0.907	0.385	0.389
1	1	1	1	0	1	1	6	1	0.902	0.385	0.385
1	0	0	1	1	0	1	4	1	0.901	0.494	0.494
0	0	1	1	1	0	1	6	1	0.875	0.549	0.555
1	1	1	1	1	1	1	20	1	0.856	0.386	0.397
0	0	0	1	0	0	1	3	0	0.849	0.417	0.420
0	0	0	0	0	0	1	3	0	0.837	0.369	0.381
1	0	0	0	0	0	1	5	0	0.818	0.311	0.319

Source: Author

There are five solutions in the presence of operational uncertainty due to energy stability and security (ESS), which results in high SPF when combined with security, Industry 4.0 and 5.0 technology capabilities, and organisational learning. Solution 6 has a high SPF in the presence of ESS when in combination with RCAS, AI, and BDA in the absence of SPSI (ESS*RCAS*~SPSI*AI*BDA). Solution 8 is in combination with RCAS, RPMR, and SPSI (ESS*OLN*RCAS*RPMR*SPSI). The other solution that would result in a high SPF is solution 9, which is ESS*~OLN*~RCAS*~RPMR*~SPSI*AI. Solution 10 and solution 11 also can lead to high SPF with the configuration ESS*OLN*RCAS*~RPMR*~SPSI*AI) and ESS*OLN*~RCAS*~RPMR*SPSI*AI, respectively. There was no necessary condition from the necessary condition analysis. The XY Plot shows that the proposition is partially supported with high $X \leq Y$ and moderate to low $X \geq Y$ (Figure 8.4)

Table 8.24: Sufficient configurations of high sustained performance in the presence of energy stability and security and industry 4.0 and 5.0 technologies capabilities and organisational learning

	Solution										
Configuration	1	2	3	4	5	6	7	8	9	10	11
ESS				○	○	●		●	●	●	●
OLN		○	●		○		●	●	○	●	●
RCAS	●	○			●	●	●	●	○	●	○
RPMR	●	○	○	●	●		○	●	○	○	○
SPSI	●		○	●	●	○		●	○	○	●
AI	●	●	●			●	●		●	●	●
BDA		○	●	●	●	●	●				
Raw coverage	0.476	0.299	0.316	0.413	0.418	0.282	0.293	0.535	0.393	0.388	0.386
Unique coverage	0.007	0.011	0.012	0.011	0.008	0.007	0.003	0.045	0.003	0.004	0.007
Consistency	0.850	0.883	0.901	0.921	0.901	0.867	0.885	0.896	0.912	0.932	0.943
Overall solution coverage	0.825										
Solution consistency	0.810										

Note: Black circles indicate the presence of conditions, and empty circles indicate the absence of condition

Large circle: core condition small circle: peripheral condition blank space: "don't care condition"

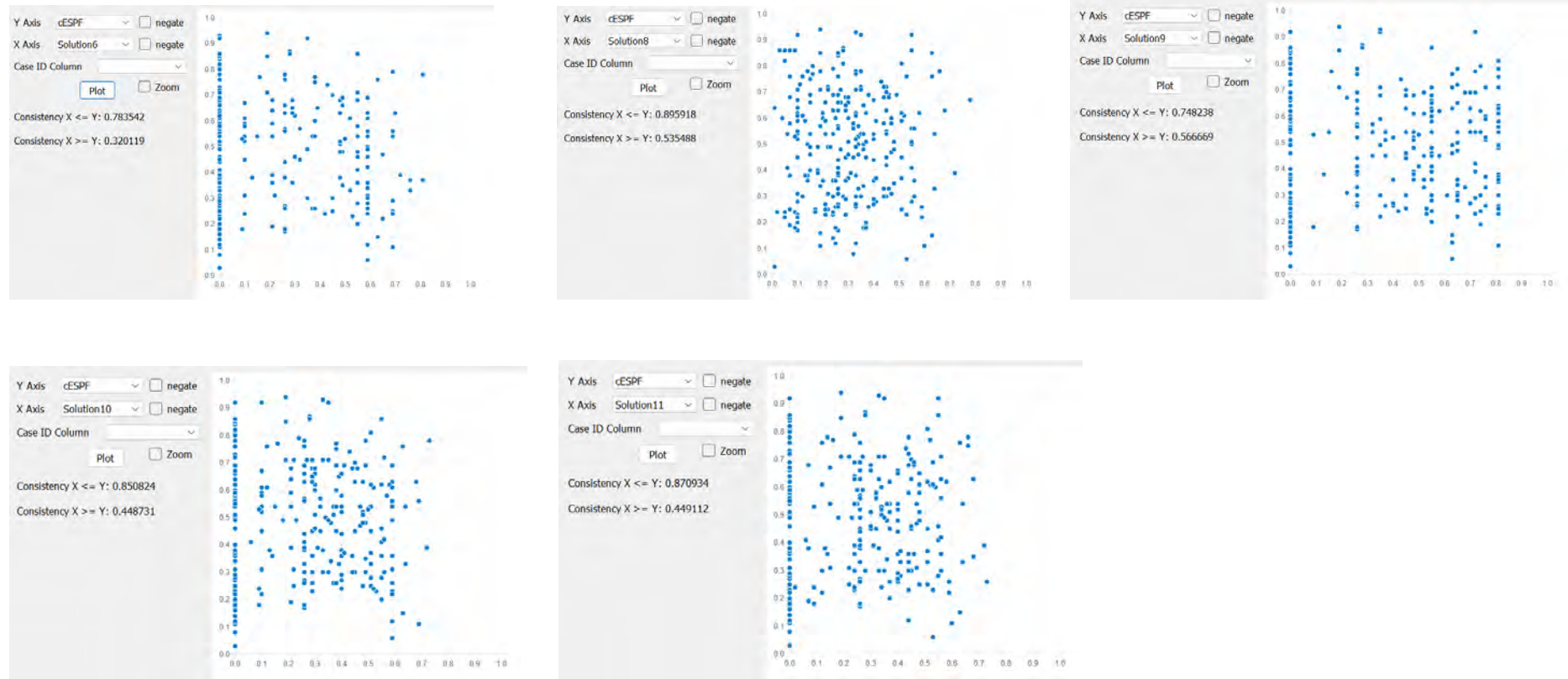


Figure 8.4: XY Plots of fsQCA for solutions with presence of ESS

8.6.3 Operational uncertainty construct

The SPSI and OLN were regarded as the core conditions as they were present in both the parsimonious and intermediate solution and had higher coverage (≥ 0.50) and consistency (≥ 0.85). The PEHS, AI, and ARVR, although they appeared in the parsimonious and intermediate solution, were still regarded as peripheral conditions as their solutions had coverage < 0.50 or coverage was < 0.85 . The intermediate solution results show that the solution coverage was 0.686 and consistency were 0.864 (Table 8.25).

Table 8.25: Sufficient configurations of high sustained performance in the presence of operational uncertainty and industry 4.0 and 5.0 technologies capabilities and organisational learning

	Configuration	Solution		
		1	2	3
Configuration for High SPF	OPU2	●	○	
	OLN	●	○	
	PEHS	○	○	
	SPSI		●	
	AI	●	●	
	ARVR	○		
	BDA		●	
	Raw coverage	0.280	0.260	
	Unique coverage	0.043	0.021	
	Consistency	0.895	0.925	
	Overall solution coverage	0.686		
	Solution consistency	0.864		
Configuration for low SPF	OPU2	○	●	●
	OLN	○		●
	PEHS	○	○	
	SPSI	●	○	○
	AI	●	●	●
	ARVR			
	BDA	●	●	●
	Raw coverage	0.255	0.304	0.301
	Unique coverage	0.011	0.001	0.001
	Consistency	0.924	0.914	0.909
	Overall solution coverage	0.636		
	Solution consistency	0.849		

High SPF

SPF = f(OPU2, OLN, PEHS, SPSI, AI, ARVR, BDA)

Low SPF

~SPF = f(cOPU2, OLN, PEHS, SPSI, AI, ARVR, BDA)

Large circle: core condition small circle: peripheral condition blank space: "don't care condition"

Thus, the solution covers about 68.6% of the cases, and solution consistency accounts for the combination of conditions consistently predicts the outcome was 86.4%. Only individual solutions were reported with coverage ≥ 0.2 and coverage ≥ 0.75 .

The solution – OPU2*OLN*~PEHS*AI*~ARVR denoted as solution 0 was used for specific proposition. This proposition looked at the presence of operational uncertainty in combination with organisational learning and artificial intelligence. The XY plot is present in Figure 8.5 showing that consistency to which the observations were plotted with $X \leq Y = 0.855$ while the $X \geq Y = 0.448$. With high $X \leq Y$ moderate to low $X \geq Y = 0.448$, indicate that proposition that is partially supported that the solution with high performance depending on large group of firm, however it does not predict all the cases thus not fully advancing the theory. Papas and Woodside (2021) posit that the consistency above 0.80 can serve theory advancement

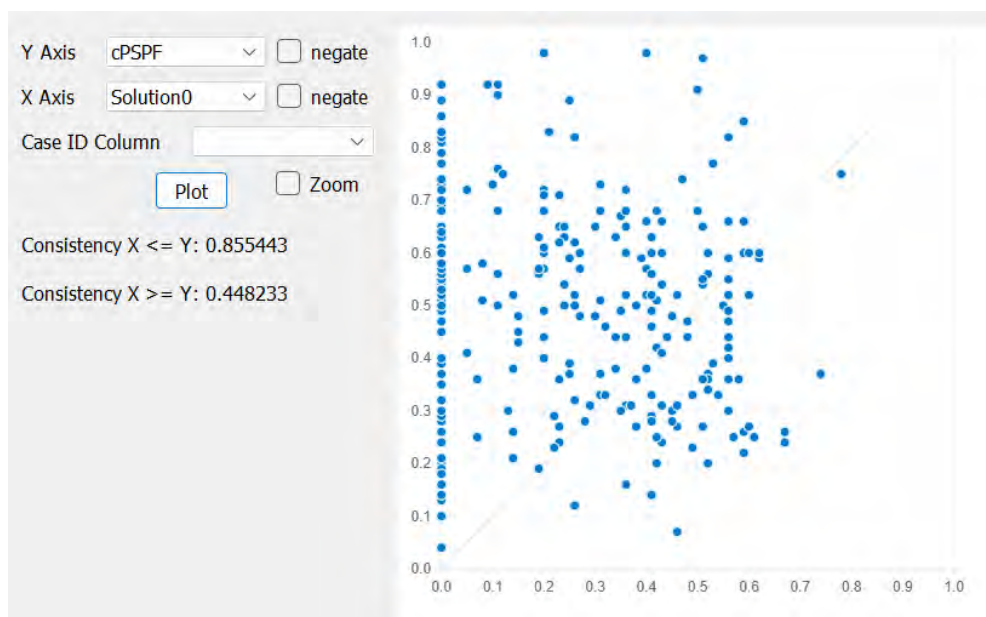


Figure 8.5: XY Plots of fsQCA for solutions with presence of OPU2

8.7 Chapter Conclusion

The results from interdependence and causal analysis further support these propositions for multidimensionality and also classify these dimensions into importance and cause and effect. The analysis identified five causal dimensions, which were growing political tension, cost-of-living-driven consumer behavioral change, pandemic turbulence, energy stability, and security uncertainty, and the entrenchment of large firms. These causal dimensions were used for PLS-SEM and fsQCA analysis, with the results showing a

negative significant relationship between the two dimensions, growing political tension and energy stability and security uncertainty with sustained performance. The fsQCA results show that there exist multiple configurations that can lead to high sustained performance.

Chapter 9 Modified neo-configurational perspective

9.1 Introduction

The combined three objectives of the research study focused on developing an operational configurational theoretical and methodological perspective for sustained firms' performance during operational uncertainty. In Chapter 6, the results linked to objective 1, related to the development of a comprehensive understanding of operational uncertainty in manufacturing, were presented and analysed, and conclusions were drawn about them. The same applied to the review and validation of the capabilities of Industry 4.0 and 5.0 in manufacturing operations in Chapter 7. Chapter 8, using relevant results, formulated and analysed sustainable performance configurations (outcomes condition) with causal conditions from operational uncertainty, Industry 4.0 and 5.0 technologies, and organisational learning.

Chapter 9 discusses these findings and compares and contrasts these findings with those presented in the literature review chapter (Chapter 2 and 3). The results are then utilised to advance a modified neo-configurational theoretical and its related methodological perspective. Wacker (1998) noted that research creates studies with long-lasting effects when they adhere to the standards of excellent theory, which can only be achieved by adhering to well-thought-out insights. These study results provide a necessary pathway to follow to evaluate whether the theory is constructed so that it is empirically refutable (falsifiability). This, together with utility, evaluates whether the theory includes both the logical, which involves scope, and the empirical, which provides for explanation and prediction. This creates a critical pathway to self-check and develops this robust adapted theory–modified neo-configurational theory perspective. Thus, this aligns with both theory and methodological advancements in this research.

9.2 Summary of key findings

The study identified the research and highlighted the research gaps. The objectives were developed and the six propositions., with key findings presented in Table 9.1.

Table 9.1: Key findings of the study

Objective	Propositions	Findings
Objective 1: Develop a comprehensive understanding of operational uncertainty in manufacturing.	Proposition 1 Operational uncertainty is a multi-dimensional construct	The results of the present study also confirm that operational uncertainty is a norm in the manufacturing industry with a Manufacturing Operational Uncertainty Index (MOUI) = 0.752, indicating the range of futures, highlighting that it is difficult to divide these futures into a discrete and exhaustive set of possibilities due to the complexity of conditions (variables) at play.
	Proposition 2: Operational uncertainty is a norm in the manufacturing sector, as not all relevant information is already known to decision-makers	The results of the study confirmed that operational uncertainty is a multi-dimensional construct with a reflective model for dimensions and reflective-reflective for higher-order construct. This means that for the dimensions, the indicators can be added or excluded in the formation of the dimension. The same is also true for construct, operational uncertainty
Objective 2: To review and validate the capabilities of fourth and fifth industrial revolution technologies in manufacturing operations and linkage to organisational learning.	Proposition 3: Industry 4.0 and 5.0 technologies capabilities can manage the operational uncertainty in the manufacturing sector	Industry 4.0 and 5.0 technologies and their capabilities can manage the operational uncertainty dimensions
	Proposition 4: Organisational learning has a positive relationship with the capabilities of Industry 4.0 and 5.0 technologies.	Organisational learning is an effective causal variable that help to managed operational uncertainty with the Industry 4.0 and 5.0 technologies.

Objective	Propositions	Findings
Objective 3: Formulate and analyse sustainable performance configurations (outcomes condition) with causal conditions - operational uncertainty, Industry 4.0 and 5.0 technologies and organisational learning.	Proposition 5: The combinations of OPU, IRT, and OLN conditions lead to high or low sustained performance.	Industry 4.0 and 5.0 technologies capable of managing operational uncertainty. This through advanced technology-driven scenario planning and supply chain integration (SPSI), flexible production and mass customisation (FPMC), real-time system and process monitoring and response (RPMR), root cause analysis and sustainable solutions (RCAS). These technologies are mainly artificial intelligence (AI), Internet of Things (IoT), big data analytics (BDA) and to a less extent advanced robotics (ARB), blockchain and augmented and virtual reality (ARVR).
	Proposition 6: Integration of optimising methods is necessary for optimum outcomes of QCA-based methods	This study offers an integrative approach of fuzzy-DEMATEL with PLS-SEM and fsQCA. The inclusion of the optimising method fuzzy-DEMATEL by identifying the causal and effect conditions This help to streamline solutions developed by the fsQCA to effectively manage operational uncertainty with Industry 4.0 and 5.0 technologies.

Source: Author

9.3 Realities of operational uncertainty in manufacturing

The first objective of the study, to develop a comprehensive understanding of operational uncertainty in manufacturing, provided a critical base for investigating and understanding these realities. The propositions guided the in-depth analyses (Bacharach, 1989; Ulaga et al., 2021) on the dimensionality and level of operational uncertainty and their resulting impacts on the operational determinants.

9.2.1 Dimensionality of operational uncertainty

Dimensionality describes the structure of the construct, representing whether the construct is composed of a single underlying dimension or multiple interrelated dimensions. It determines how the construct is conceptualised, operationalised, and analysed. Understanding the dimensionality of a construct is essential for accurate measurement and ensuring meaningful representation and interpretation. The present study investigated the dimensionality of the operational uncertainty with the proposition indicating that it was a multidimensional construct. The study's results revealed that operational uncertainty is a multidimensional construct, thus confirming the assertions of Sniazhko (2019) and a need to develop this multidimensional construct.

In the present study, the operational uncertainty construct was developed from nine theoretically constructed dimensions of uncertainty. The nine theoretical dimensions of uncertainty employed in the empirical analysis with each dimension capturing a unique aspect of the construct, and together, they provide a comprehensive understanding of it. For the external operating environment, these were: geopolitical tension, policy, and regulatory uncertainty, cost of living-driven consumer behavioural change, and pandemic turbulence and energy stability and security. At the industry level, these sources of uncertainty include skills for future work and the entrenchment power of large firms, while at the firm level, sources of uncertainty involve generational work behaviour and ethics and process capability and variations. As shown in the present research results the multidimensional construct was validated with various operational uncertainty analyses including: a scatter plot (Nguyen et al., 2020), corrected item-total correlation (Zijlmans et al., 2019), measurement model of lower-order dimensions. Testing this multidimensional construct involved a comprehensive approach that considers the complexity and interrelated dimensions of the construct. This process typically includes the

development of a measurement model, validating the construct, and using statistical methods to ensure reliability and validity. The multidimensionality of operational uncertainty was confirmed with a PLS_SEM measurement model with the results of the lower-order constructs (dimension) confirmed with the reliability (Cronbach alpha) together with composite reliability, (ρ_c) and (ρ_A) (Dijkstra & Henseler, 2015). Additionally, the validity of the model was confirmed for convergence validity with the average variance extracted method. These results were also analysed for discriminant validity using the Fornell-Larcker Criterion (1981), cross-loadings, and the Heterotrait-Monotrait criterion (HTMT) (Henseler et al., 2015). This multidimensional construct was operationalised in this research using a second-order construct model, also known as the higher-order construct model (Cao & Huang, 2023). Higher-order constructs allow for modelling at an abstract level, integrating more concrete subdimensions. This was important, as Lambert and Newman (2023) argued that in the absence of evidence supporting that measures accurately represent their intended constructs, research risk bias, misleading results, or incorrect conclusions in tests of theoretical relationships.

9.2.2 Level of operational uncertainty in manufacturing

The results show that different dimensions influence high levels of operational uncertainty, which is the norm in the manufacturing sector. Based on the developed and validated total composite score index, this study's overall level of operational uncertainty was classified as a range of futures. This was due to the complexity of the variables at play; as such, it is not possible to divide these futures into a discrete and exhaustive set of possibilities, yet there are additional alternative futures that are crucial to the decision (Courtney, 2001; Millet, 2002; Walker et al., 2003). In this level of complexity, the mechanisms that will bring about certain future conditions cannot be simply specified, making it impossible to calculate the precise probability of future events. This is aligned with views of several authors who posited that the operational uncertainty is a significant global business phenomenon (Mikaelian, 2010; Sniazhko, 2019; Sniazhko, 2021). With this resulting in many challenges in manufacturing firms regarding goods availability, high prices, labour affordability, reliability, maintenance, knowledge retention, lower sales, and changing customer preferences (Ambulkar et al., 2015; Leung & Sun, 2021). Understanding the levels of uncertainty is important for manufacturing firms to make effective decisions (Walker et al., 2003). Adeptly managing and minimising these uncertainties can transform them into opportunities for competitive advantage. This will

go a long way toward the response required to address operations management problems driven by complexity emanating from operational uncertainty. As noted early in this report, this is particularly urgent for the manufacturing sector in South Africa and most African countries.

9.2.3 Operational uncertainty on operations

The operational uncertainty dimensions can individually or collectively negatively impact manufacturing operations. The study identified eight operations determinants in manufacturing. These were supply chain disruption, increased cost of production, market access restrictions, fluctuation of currency value, change in customer demand, restricted labour availability and productivity, quality of the product, and compromised knowledge management.

Supply chain disruption. The findings of the present study showed that the supply chain is disrupted by multiple operational uncertainty dimensions, including growing geopolitical tension, cost-of-living-driven consumer behavioural change, pandemic turbulence, inadequate energy stability and security, entrenchment power of large firms, and, to a lesser extent, skills for future industrial work. In addition, more recently, the war in the Middle East has disrupted the supply chains which resulted in a blockade in Suez and Panama Canals creating a big challenge for goods movement involving this shortest maritime route between Asia and Europe (IMF PortWatch, 2024).

Pandemic turbulence was another cause with a broad disrupting impact. Santacreu and LaBelle (2022) highlighted that the manufacturing sector experienced heterogeneous cost increases during the pandemic, with industries such as Coke and Petroleum seeing the highest price hikes. These increases were driven by supply chain disruptions, contributing to rapid producer price inflation (PPI). This is congruent with findings from the literature showing that COVID-19, in particular, disrupts everything from small to large firms (Chhatwani et al., 2022; Belitski et al., 2022).

Cost of product. At the same time, the increased cost of the product is linked to other dynamics, such as supply chain disruptions, which are impacted by growing geopolitical tension, pandemic turbulence, the entrenchment of large firms, and process capability and variations. The COVID-19 pandemic highly impacted global supply chains (Kumar et al., 2020), including industries in South Africa as well as the wider African continent

(Anakpo & Mishi, 2021). Another cause was inadequate energy stability and security. South Africa struggled with a lack of energy stability and security. Electricity loadshedding in South Africa has a profound impact on the manufacturing sector, leading to operational disruptions, financial losses, and reduced productivity. The manufacturing industry, heavily dependent on a stable electricity supply, faces significant challenges due to frequent power cuts. These disruptions affect production schedules and lead to increased operational costs and potential job losses (Dewa et al., 2020). This was relatively worse for small and medium enterprises (SMEs) in the manufacturing sector, which remained particularly vulnerable, with many experiencing significant financial losses and even closures due to their reliance on the national grid and limited access to alternative energy sources (Madumi, 2023). Olanrewaju (2019) argued that the availability of a stable energy supply is closely related to economic and industrial sustainability. This is particularly true as some of the manufacturing industry require considerable amounts of energy for performance and survival. Kan et al. (2020) also highlighted that the South African manufacturing industries, particularly the basic iron and steel, petroleum, chemical and chemical products, and textile industries, have contributed to current industrialisation in the country and remain among the most energy-intensive industries.

Market access restriction. The present study's findings also revealed that the growing geopolitical tension, policy and regulatory uncertainty, and pandemic turbulence have resulted in market restrictions. This disruption came about due to barriers to trade, restricted access to essential materials, and increasing transportation costs. This leads amongst others to complex customs processes and higher tariffs, causing delays and increased costs for firms reliant on international supply chains. Zeng et al (2022) showed that bilateral tensions and the trade war between USA and China have hit sectors hard, particularly those with well-established supply chain links to China, and this has had a domino effect on trading partners of these countries, such as South Africa in the case of China. This research also highlighted the impact of large firms' entrenchment power, which results in supply chain disruption, an increase in the cost of production, and market restrictions. This supports earlier findings of Li et al. (2021), who argued that large firms often use their market power to maintain dominance. The large firm can disrupt the supply chain by shaping decision-making processes, competitive dynamics, and performance outcomes. These large firms often leverage their economic power to dominate negotiations, impose favorable terms, and influence supply chain configurations

(Reynolds, 2024). In addition, large firms tend to possess significant political and economic power, which can be used to influence market rules and regulations. This power can lead to market restrictions by shaping policies that favour entrenched interests over competitive market forces (Zingales, 2017).

Fluctuation of currency value. Similarly to the market access restriction, the findings of the present study revealed that currency value fluctuation is impacted by growing geopolitical tensions, pandemic turbulence, and, to a lesser extent, policy and regulatory uncertainty. Bednarski (2023) acknowledged that there is a supply chain disruption due to growing geopolitical tensions, confirming different studies of this, such as Ali et al. (2024) and Bednarski (2023). These authors acknowledge that practically every industry and firm was being impacted by supply bottlenecks, resulting in increased purchasing prices. European gas and oil disruptions and increased inflation rates exacerbated these changes. South Africa and key trading partners such as Germany saw an increase in supply lead time and purchase prices that affected the economies of both countries (KPMG, 2022). PwC's (2024) South Africa manufacturing analysis also highlighted the supply chain disruption as the major factor in manufacturing sector.

Customer demand is impacted by cost-of-living-driven consumer behaviour change, pandemic turbulence, and inadequate energy stability. The results of this study also indicated that cost-of-living-driven consumer behavioural change is another cause of operational uncertainty. This is not surprising, as Wiersma et al. (2020) explained that it has resulted in reduced spending as the most common response to financial challenges. Abe and Mugobo (2021) posited that changing preferences are evident in consumers from developing countries such as South Africa, who follow the global phenomenon of trading down by buying cheaper brands or privately labelled products over their favourite brands. Changes in consumer demand significantly impact manufacturing processes, necessitating adaptations in production and supply chain management. For example, at the height of the COVID-19 pandemic, manufacturers had to adjust procurement and delivery processes to meet fluctuating demands. Manufacturers were also required to adapt to these shifts by providing a diverse range of products and adjusting order sizes. Manufacturers are increasingly adjusting their order sizes in response to evolving consumer demands, driven by factors such as demand for product variety, quality, and flexibility. These changes are reshaping the dynamics between manufacturers and retailers, as well as impacting operational processes within manufacturing firms.

Labour availability and productivity are restricted by skills for future industrial work and, to a lesser extent, policy and regulation uncertainty. What is evident is that there is a high variability of policy uncertainty, which affects the manufacturing sector. Policy uncertainty can have a positive effect on structural upgrading in manufacturing, pushing firms towards service transformation and vertical integration, especially in regions with advanced manufacturing structures such as China (Hu & Yan, 2021). At the same time, policy can hinder operational efficiency and investment in manufacturing, where it can also drive structural changes and strategic shifts in certain contexts. The results in this research revealed that policy and regulatory uncertainty result in market restriction, as well as fluctuation of currency value and restructured labour availability and productivity

Quality of the product is impacted by pandemic turbulence, generational work behaviour and ethics as well as process capability and variations. The results also indicated that variations in generational work behaviour and ethics (GWB) were effect dimensions. This dimension is shown to have an effect on the quality of the product and to compromise knowledge management. This is not surprising, as in the workplace today (2024) there will be up to four generations - Baby Boomers, Generation Xers, Generation Yers or Millennials and Generation Zers (Heyns & Kerr, 2018; Smeak, 2020). Heyns and Kerr (2018) argued that a variety of human factors enter the workforce along with staff that span multiple generations. These factors significantly impact the culture of a firm and the workplace. Intergenerational differences significantly affect workforce dynamics and organisational management, presenting both challenges and opportunities. These differences arise from distinct values, experiences, and attitudes shaped by unique historical, political, and social events for each generation. Each generation exhibits distinct characteristics in core values, technology use and social values, which influence their work ethics (Manongcarang & Guimba, 2024). Process capability and variations significantly contribute to operational uncertainty in manufacturing by affecting the quality, reliability, and performance of products. In the manufacturing industry, process capabilities and variations play dual roles as causes and effects. Variations can disrupt production efficiency and reduce process capabilities, while poor capabilities exacerbate variations and defects.

Knowledge management is impacted by skills for future industrial work and generational work behaviour and ethics. Generational differences can also contribute to skills mismatches within the workforce, which requires approaches that will enable customised

training programs and regular skills assessments to bridge these gaps (Naliaka & Ngui, 2024). These would have an influence on knowledge management, especially if the knowledge sender-receiver relationship is not managed as well as knowledge preservation. The other effect based on this research was operational uncertainty due to the skills required for future work (SFW). Similar to generational work behaviour and ethics, the results showed that this compromises knowledge management and restricts labour availability and productivity. Integrating future work skills into manufacturing environments introduces operational uncertainty due to the dynamic interplay between human and machine capabilities, evolving skill requirements, and the complexity of modern manufacturing systems. This complexity can lead to operational uncertainties as workers must adapt to new roles and interactions with machines. A significant gap exists between current workforce skills and the skills needed for future manufacturing environments. This mismatch creates uncertainty as firms struggle to find qualified personnel to meet the demands of advanced manufacturing processes (Penesis et al., 2017).

It was evident that operational uncertainty brought complexity to operations. Simply put, operational uncertainty has multiple dimensions that impact and influence multiple aspects of operations. For example, growing geopolitical tension results in supply chain disruption, increased cost of production, market access restrictions, and currency value fluctuation. As such, these impacts are related and overlap. They cannot be looked at narrowly, as operational uncertainty dimensions can affect multiple aspects of operations, possibly having a domino effect on others.

9.4 Use and capabilities of Industry 4.0 and 5.0 technologies in manufacturing

The second objective was to review and validate the capabilities of Industry 4.0 and 5.0 industrial revolution technologies in manufacturing operations. The literature review identified eight Industry 4.0 and 5.0 technologies in use in the manufacturing sector (Garg et al., 2022; Koh, 2019; Noble et al., 2022). As explained earlier in Chapter 1, there were eight technologies that were included as part of this study. These were the Internet of Things (IoT), artificial intelligence (AI), big data analytics, (BDA) robotics and advanced robotics (ARB), additive manufacturing (3D printing) (ADM), blockchain (BCC), augmented and virtual reality (ARVR), and quantum computing (QCP). The firm indicated

the level of use of these technologies, and the state of use of technologies with a set of available capability. The matching of capabilities and Industry 4.0 and 5.0 technologies was done by the experts and this data was triangulated.

9.4.1 Industry 4.0 and 5.0 technologies and use in manufacturing

The results of the empirical analysis of the present study revealed that IoT, AI and BDA were in high use, with more than 70% of manufacturing firms indicating that they were using these technologies. A high rate indicated the widespread use of IoT in manufacturing. The high usage can be attributed to IoT's ability to enhance operational efficiency, improve data collection, and enable predictive maintenance, reducing downtime and costs. Therefore, the IoT is often viewed as a foundational technology for Industry 4.0, where connected devices and smart sensors help firms automate and optimise processes (Kumar et al., 2019). The broad applicability across sectors drives high adoption, as IoT facilitates real-time monitoring and control of assets. The use of AI is commendable from these manufacturing firms. This is because automation is enhanced through IoT by integrating AI, which allows machines to perform tasks autonomously, reducing the need for human intervention and increasing production speed (Abdullayev et al., 2024; Chaurasia et al., 2023). The IoT systems collect vast amounts of data which are processed to generate actionable insights. These insights support informed decision-making, improving operational efficiency, and strategic planning (Varghese & Shereef, 2024). The use of artificial intelligence (AI) can assist manufacturing in promoting human-machine collaboration. It can help with process optimisation and automation, quality control and inspection, and supply chain management. AI enhances quality control through advanced computer vision and image recognition technologies, which are used for real-time product inspections and defect detection to improve product quality and reduce waste. Big data analytics is also noted in the findings in this study. Using big data analytics (BDA) tools empowers firms to effectively handle and analyse extensive volumes of data to identify patterns, trends, and correlations (O'Donovan et al., 2015). This information has the potential to provide valuable insights into making strategic decisions, improving operational efficiency, and enhancing customer satisfaction (Sahoo, 2021; Bi et al., 2021), a necessity especially in responding to operational uncertainty and creating a high-performance firm with sustained performance.

It is noted from the findings that there was a moderate use of advanced robotics and low use of blockchain, Augmented and virtual reality, additive manufacturing (3D printing),

and quantum computing in these manufacturing firms. This was not a complete surprise, as the investment cost cybersecurity risk (Mohammed et al., 2024), and expected skills for using these technologies are high. The challenges from cybersecurity risks emanate from its lack of security, its outdated nature, and its high vulnerability to attack. The other challenge is the attempt to secure the data, which can result in data manipulations affecting decision-making (Toussaint et al., 2024), or it can create problems for firms and result in business loss. It is also plausible to have a high use of technologies such as IoT and AI, as they are considered cost-effective and help optimise resource use and operational performance (Elegbeleye et al., 2024).

The low use means that manufacturing firms are missing out on some of the important advances that technology can leverage. These include advances such as rapid prototypes and extensive customisation, allowing the production of tailored products to meet specific consumer needs (Öberg, 2023), a need during times of high competition operating environment with high levels of operational uncertainty. Others, such as augment and virtual reality and blockchain, can even respond to the firms needs. The utilisation of augmented reality and virtual reality technology denoted as ARVR offers immersive experiences and simulations that have the potential to enhance training (Adhershini et al, 2024). Blockchain technology facilitates enhanced transparency and security in transactions and data management (Cao et al., 2024).

The South African manufacturing analysis 2024 by PwC (PwC, 2024) showed that digital transformation is reshaping the sector with Industry 4.0 technologies. It further states that smart factory technologies drive the significance of manufacturing efficiency and sustainability. These technologies are central to the concept of Industry 4.0, which emphasizes the digitalisation of manufacturing processes. This is especially important since smart technologies enable a high degree of automation, connectivity, and data-driven decision-making within manufacturing environments (Shahab et al., 2024; Wang, 2023). These technologies are central to the advancement of Industry 4.0, which emphasises the digitalisation of manufacturing processes.

9.4.2 Capabilities of Industry 4.0 and 5.0 technologies in manufacturing

The findings also confirmed that the different capabilities of Industry 4.0 and 5.0 technologies with the survey confirmed their reliability, while the experts aligned these capabilities depicted on a heat map. The results of the empirical analysis results in this

research show that 19 of the 20 Industry 4.0 and 5.0 technologies manufacturing capabilities are constituted into six themes or groups. The six groups had internal consistency reliability with the Cronbach Alpha coefficient, $\alpha > 0.60$. These include scenario planning and future prediction (SPFP), supply chain integration and collaboration (SCIC), flexible production and mass customisation (FPMC), real-time system and process monitoring and response (RPMR), root cause analysis and sustainable solutions (RCAS), and protective ecosystem (humans and systems) (PEHS). In the modelling analysis, SPFP and SCIC had lack of discriminant validity and were combined to scenario planning and supply chain integration (SPSI). Scenario planning can be effective because it involves the development of comprehensive and credible depictions of potential future outcomes (Cordova-Pozo & Rouwette, 2023). Industry 4.0 technologies offer advanced tools for the study, simulation, and visualisation of data, facilitating the development of increasingly complicated scenarios. Suwunnamek, 2022). In addition, AI analysis of such data allows the identification of patterns and trends that may not be readily discernible by human observation. The IoT can also be used to observe patterns and construct scenarios grounded in factual performance and environmental information (Ahmetoglu et al., 2023). Integrating various systems and processes can lead to enhanced efficiency, cost reduction, increased transparency, and improved customer service (Koh, 2019). Integrating data from diverse sources is critical to generating insights, informing decision-making, and implementing advanced collaboration platforms to enhance communication and coordination among various stakeholders (Ajayi & Laseinde, 2023).

Additionally, the results show that the Industry 4.0 and 5.0 technologies were capable to effect flexible production and mass customisation. This was important because manufacturing firms must respond effectively to dynamic market conditions and operational uncertainties with flexible production and mass customisation (Höse et al., 2023). Industry 4.0 technologies create personalised relationships with customers, optimise production chains, and make businesses more efficient (Liao et al., 2018; Schwab, 2017). At the same time, it can help with customer need with the business being effective root cause analysis, as it supports the resilience of production systems (Ito et al., 2022). Having this capability is critical as root cause analysis is time consuming, particularly when dealing with a substantial volume of data pertaining to the manufacturing operation. These capabilities that can be leveraged from Industry 4.0 and

5.0 technologies provide firms with tools never before seen, allowing them to understand, emulate, and improve their operations. As these technologies develop and integrate, the landscape of firm operations continues to change, becoming more efficient, responsive, and customisable. Firms that can generate manufacturing information using real-time data to provide precise and prompt decision-making processes that can produce beneficial outcomes for the entire business (Kang, 2022).

9.4.3 Capabilities of Industry 4.0 and 5.0 and organisational learning

The findings in this present study confirm that organisational learning has a positive relationship with the capabilities of Industry 4.0 and 5.0 technologies, with five of the six dimensions of capabilities having a statistically significant relationship. This confirms the linkage and importance of organisational learning on capabilities of Industry 4.0 and 5.0 technologies. This is important as there are several factors that can influence the effectiveness of technological implementation. This ranges from inadequate knowledge and application, external pressure resulting in forced accelerations of implementation such as competition and survival (Sinha & Noble, 2008) and pandemic-induced changes (Patanjali & Bhatta, 2022). These are said to contribute towards the variations in the effectiveness of the firm's implemented technologies.

The learning process involves utilising people's experience and practical knowledge as valuable assets for implementing, advancing, and incorporating innovative technologies. This process encompasses the dual aspects of knowledge exploration and exploitation. The attainment of a favourable equilibrium between learning endeavours aimed at maximising the utilisation of existing knowledge (exploitation) and the allocation of resources towards the creation of novel knowledge (exploration). Adopting a novel perspective when conceptualising organisations, management, and change is imperative to navigate a dynamic operational environment. This involves fostering active learning pathways and trajectories while striving for increased levels of adaptive knowledge transfer (Ivaldi et al., 2022). This is necessary when adopting and using industry 4.0 and 5.0 technologies so that they can be effective for sustained performance.

9.5 Managing operational uncertainty in manufacturing with the Fourth and Fifth Industrial Revolution Technologies

9.5.1 Managing operational uncertainty due growing geopolitical tension

The third objective focused on formulating and analysing sustainable performance configurations (outcomes condition) with causal conditions from operational uncertainty, Industry 4.0 and 5.0 technologies, and organisational learning. The integrated approach was useful in this present study as the fuzzy DEMATEL separated the nine dimensions into causes and effects. This multicriteria decision making method is useful for visualising the structure of complex causal-effect relationships (López-Ospina et al., 2022). In this study, the Fuzzy-DEMATEL highlighted the dominant relationships between factors and the interdependencies to effectively prioritise responses to operational uncertainty. The results of the present study identified the causal dimensions: geopolitical tension, cost-of-living-driven consumer behavioural change, pandemic turbulence, energy stability and security, and the power of large firms. The effect conditions were skills for future work, generational work behaviour and ethics, process capability and variations and policy and regulatory uncertainty. Noticeably, all the dimensions of the external environment were causes except for the policy and regulatory uncertainty. The PLS-SEM structural model, the results show that of the five causal dimensions, there was a statistically significant negative relationship between geopolitical tension and sustained performance and between operational uncertainty due to inadequate energy stability and security. The other three were not significant. When all five causal conditions combined, forming operational uncertainty (OPU2), it had a statistically negative relationship with sustained performance.

Growing geopolitical tensions is one of the important dimensions of operational uncertainty, and the results in the present study have revealed that firms have actually listed it as the main issue regarding uncertainty, assigning it with the highest relative importance index. Also, when it came to the analysis with fuzzy-DEMATEL, it was evident that it was one of the main causes, according to experts. It is one of those dimensions that showed a direct relationship with the performance of the firms. At the same time, it showed that there is a need to form configuration as part of the important outcomes in order to resolve these critical causal conditions that are creating a challenge to manufacturing firms. This result is not surprising, as it is evident that the world has

become less united and different firms are being formed, with different countries forming new alliances. This was happening because of the growing tensions that were taking place, especially in the Middle East, Europe, and Asia. In 2022, in Europe, this tension that started in 2014 between Russia and Ukraine burst into a full-fledged war (Levy & Leaning, 2022).

This resulted in Russia being sanctioned and with Russia being the main exporter of gas to Europe, some EU countries are now struggling with high energy levels but a large supply chain disruption. This was further exacerbated by the tension and subsequent wars in the Middle East led by Israel against Palestine and now recently against Lebanon and the exchange of attacks between Israel and Iran, and more importantly, what is happening within the Mediterranean Sea where Yemen is blocking the movement of the shipping vessels (Faucon et al., 2023). This has resulted in this disruption of the supply chain where the turn-around has been higher, also where in terms of the deliveries instead of going through the Mediterranean Sea vessels especially aligned to the west and Israel in particular and others have to go through South Africa, the Cape of Good Hope. It meant that there is a delay in the deliveries and the cost implication is higher (IMF PortWatch, 2024). The maritime sector has alluded to the fact that some of the operational costs have increased by more than 30% (IMF PortWatch, 2024).

This has meant that most of this cost will be transferred to the customers, which significantly impacts the manufacturing sector, especially when it comes to spare parts and other raw materials or as part of the production process. Additionally, there are also challenges that are occurring with the growing relationship between Russia and China. Trade wars between America and China and more recently Europe and China with tariffs being implemented make that exchange less competitive, considering Europe. In doing the same for electric vehicles that are produced in China. This is happening back where the main trading partners for South Africa are China, India, the United States and Germany, which, with the exception of India, are all entangled in geopolitical tensions. The USA and Germany are entangled in the Russia - Ukraine war and sanctioned by the G7 and the Western Countries, as well as the European Union.

There is a great challenge that will see a domino effect creating uncertainty within the South African manufacturing industry, affecting the cost of goods and the availability of other elements that are affected by or disrupt the supply chain. This meant that there

was a need to improve and manage the effects of geopolitical tension, which can be managed through the reduction of uncertainty. The fourth and fifth industrial technologies are central to the effort to improve industry performance. Experts indicated that the effects of challenges related to geopolitical tension can be mitigated with the Internet of Things, artificial intelligence and quantum computing. This can create a certain level of uncertainty and within that environment allow for an improvement in management in this complex operating environment.

The findings of the present study show six solutions that are candidates to achieve high sustained performance in the absence of growing political tension. This scenario is highly unlikely at this stage. There are four solutions that show high performance in the presence of growing political tensions. These include the use of artificial intelligence or the use of AI in combination with technologies that can enable flexible production (FPMC) and mass customisation and organisation learning conditions to manage the geopolitical. The other solution is the use of technologies AI with other technologies capable of scenario planning and supply chain integration (SPSI), flexible production, and mass customisation.

9.5.2 Managing operational uncertainty of energy stability and security

The operational uncertainty of energy stability and security is one of the other critical dimensions of operational uncertainty. The availability of a stable energy supply is closely linked to economic and industrial sustainability (Olanrewaju, 2019). South African manufacturing industries, particularly the basic iron and steel, petroleum, and chemical products and textile industries, have contributed to current industrialisation in the country and remain among the most energy-intensive industries (Kan et al., 2020). Dewa et al. (2020) explained that unstable energy supply (loadshedding) had resulted in manufacturing sector experiencing production halts and increased downtime, which compromises delivery schedules and overall productivity. Mashapu and Mathaba (2024) reported that in some cases load-shedding has led to a substantial increase in operational costs.

Considering the results of the present study in total, it is evident that this dimension is dynamic and fluid. When looking at the relative importance index, this dimension was listed as number five, which is significant given its importance to operational uncertainty affecting business firms. This may be due to three factors. One is the timing of the research, where a large majority of the surveys took place. The load shedding has since

improved and recently reached about 200 days since around February 2024 which means that there were the first signs of improvement in a stable electricity supply. The second factor is that the extent of load shedding within the past two years forced firms to make alternative energy supply plans. So now, load shedding, as much as it has negatively impacted industry performance, it has started to stabilise to some extent.

Third, firms have since migrated towards an alternative energy source, especially renewables. This is also partly evident and aligned with what is happening with lower levels of sales or demands of electricity compared to the past, with the highest demands largely remaining within households and less so in industry. It is evident in sectors that require a lot of energy, such as the manufacturing and mining industries, that while operational uncertainty exists in firms, it may be changing for the better. However, the Ministry of Energy has alluded to the fact that load shedding is not off the table in terms of energy stability, and as such, there might be a future wave of load shedding. Eskom indicated enough energy security in the next 5 years, which means that firms need to still take this operational uncertainty quite seriously, as it has impacted so negatively on many firms, especially the smaller and medium firms.

The results from the present study analysis yielded five solutions that can lead to high sustained performance in the presence of operational uncertainty due to energy stability and security. This can be achieved when combined with root cause analysis and sustainable solutions, with artificial intelligence and big data analytics. It can also be achieved in the presence of ESS in combination with scenario planning and supply chain integration, root cause analysis and sustainable solutions, real-time monitoring and response, and organisational learning. The other alternative is the presence of AI and others in AI, organisational learning, root cause analysis, and sustainable solutions. There is also an option of quantum computing, but this might depend on the complexity of the problem that needs root cause analysis.

9.5.3 Managing operational uncertainty with combined causal dimensions

The solution that was produced in this study looked at the presence of operational uncertainty in combination with organisational learning and artificial intelligence. This configuration is similar to some of the configurations proposed for other scenarios

In summary, AI, FPMC and SPSI can potentially help to manage the operational uncertainty due to geopolitical tensions. SPSI and FPMC are mainly facilitated by the AI, IoT and Blockchain. At the same time the analysis shows that to effectively manage the operational uncertainty of energy stability and security, the firm needs technologies capable of scenario planning and supply chain integration, real-time system and process monitoring, root cause analysis and sustainable solutions, with AI and BDA. In addition, augmented reality (AR) and virtual reality (VR). AR and VR can be used for different training experiences and applications (Holuša et al., 2023; Xie et al., 2021).

PwC (2024) South Africa manufacturing analysis highlights the steps the manufacturing firm can implement to improve their business, including strengthening the supply chain. This augurs well as a response to growing geopolitical tensions, which are central in supply chain disruptions. Industry 4.0 and 5.0 technologies are central in strengthening the supply chain with a report highlighting that the “Digital twins, the internet of things (IoT), and specifically sensors, robotics, artificial intelligence (AI) and decision intelligence systems have already had a positive impact on supply chain management as businesses look for ways to drive operations and cost efficiency as well as ways to reduce supply chain risk caused by disruptions” (PwC, 2024, p.10).

These assertions are in agreement with the solutions from fsQCA for sustained performance during the time of growing geopolitical tensions, which are combinations of Industry 4.0 and 5.0 capabilities and organisational learning. This finding can also have implications for other countries in Africa that are faced with the same domino effect due to dependency to the countries that are entangled in these wars. Also, these findings may have learnings and implications for other countries facing challenges of energy instability. In addition, to South Africa (Kock & Govender, 2021; Viljoen & Dube, 2023) the other countries in Nigeria (Adeshina et al., 2024), Zimbabwe (Akpan, 2024), Bulgaria, and Romania (Murăraşu & Bujor, 2022) (Murăraşu & Bujor, 2022) among others. This is aligned with the relevance of the study in African countries.

9.6 Modified neo-configurational perspective

9.6.1 Framework of the study

A framework was developed in this study which provides the outcome of the configurations model from Chapter 4 (Figure 9.1).

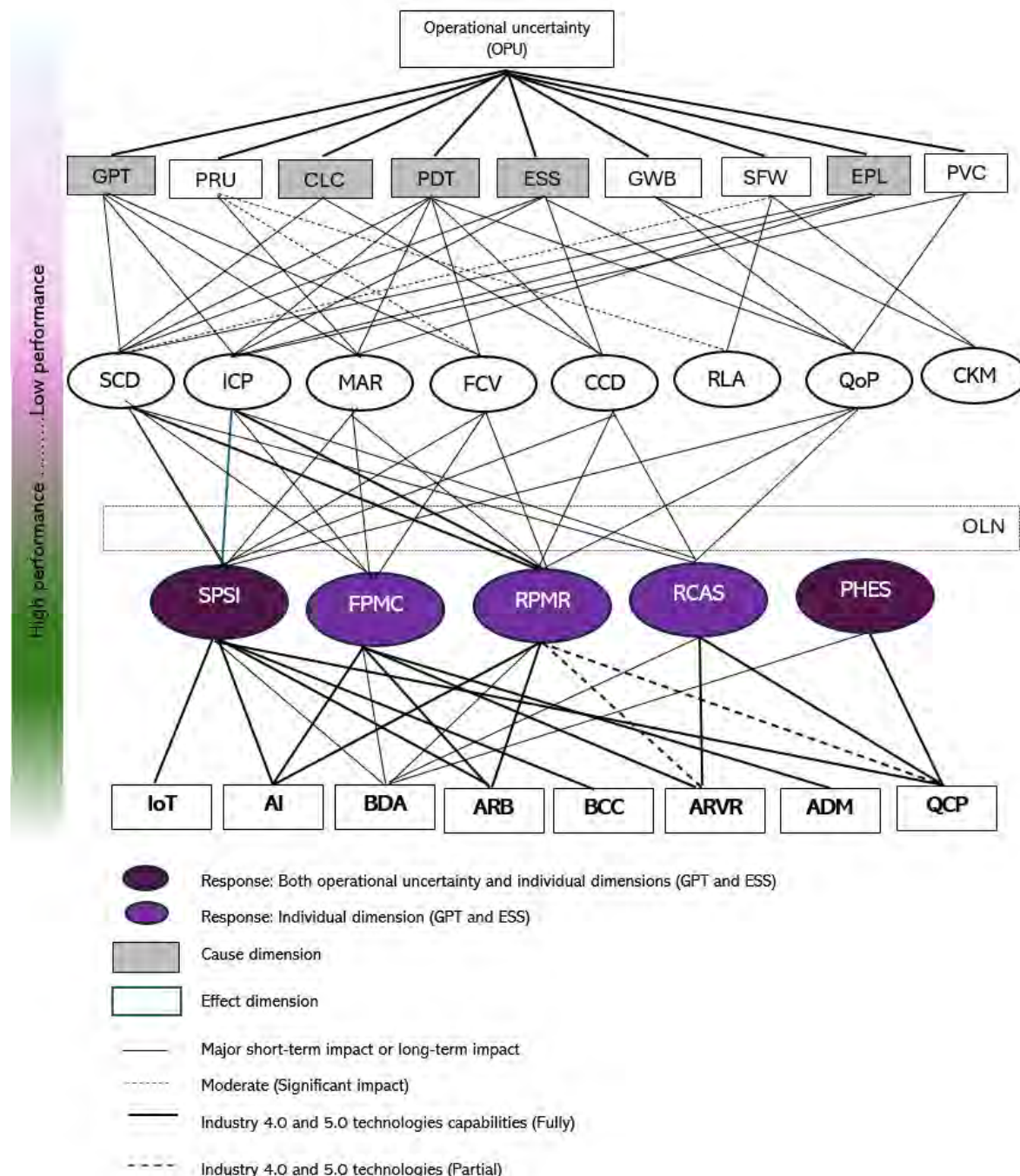


Figure 9.1: Framework of analysis of operational uncertainty

Source: Author

This starts with the existence of operational uncertainty showing how the associated dimensions influence manufacturing operations from supply chain disruption through increase in the cost of production, market access restrictions to compromise knowledge management. Industry 4.0 and 5.0 technologies are available to business managers who can use these technologies to manage these operational determinants. This analysis leads to operational improvement and sustained high performance with particular configurations.

9.6.2 Theoretical and methodological perspective

The present research focused on theory extension, using an integrated approach which allowed modification of the neo-configurational theory proposed by Misangyi et al. (2017) within the area of operations management in the manufacturing sector.

Misangyi et al. (2017) argued that QCA emerged as part of the second wave of configurational management development. This is to deal with the "void in tools capable of fully capturing causal complexity [as] conventional correlation-based approaches are not designed to address conjunctural, equifinal, and asymmetrical causal relations" (Misangyi et al., 2017, p. 256). Miller (2018) acknowledged the work of Misangyi et al. and other related work, but deemed the new approach deviating from the older approaches to configuration theorising. Despite this, the author acknowledged the necessity and development in the new approach. To obtain the benefit of the new approach, while retain the conceptualisation of the older approach, Miller (2018) advised that the new approach needed strengthening. This as the objective of older approach "were to develop conceptual typologies or to inductively derive empirical taxonomies that identify and differentiate important types of organisational phenomena, typically objective and observable, sometimes perceptual or ideological".

Miller (2018, p. 461 – 464) acknowledged that "typologies may miss the novel insights that come from empirical research " and recommended strengthening empirical research using QCA, using theory and conceptual debates to guide the research, employing case narratives to guide research scope and interpret profiles, blending quantitative and qualitative analyses, and establishing the significance of configurations, amongst other things. (Greckhamer et al. (2018, p492) confirmed that the neo-configurational perspective was driven by a set-analytic approach and went further by explaining that unlike Miller (2018), the "neo-configurational perspective is "scale-free" because it

applies not only to the organizational level but also to phenomena at the intra-organizational and supra-organisational levels. Despite this, these authors agree with the recommendations of Miller (2018) and is a view to which the present study subscribes, by looking at operational uncertainty within not only the external environment, but also at uncertainty with the industry and the individual business firm level. Thus, this study discusses the modified theoretical perspective from the premise of the neo-configurational theory, while also considering some of the recommendations of the Miller (2018) and the response of Greckhamer et al. (2018).

This study employed an integrated approach of fuzzy-DEMATEL with PLS-SEM and QCA for the modified neo-configurational theory. The fuzzy-DEMATEL is a useful hybrid approach that not only integrates both qualitative and quantitative data but it also leverages fuzzy logic to handle the inherent uncertainty and subjectivity in qualitative assessments (Lin, 2014; Lin & Wu, 2008; Yeh & Huang, 2014). The research method used in the present study obtained qualitative evaluations from experts, which were then integrated with quantitative data to form a comprehensive analysis framework (Jin, 2022). The outcomes of the fuzzy-DEMATEL allowed for a rich qualitative assessment – provided by experts working in the manufacturing sector as consultants, academics, and policymakers, all contributing competence and experience. Such analysis allowed separation of cause from effect, especially for some of the dimensions that can easily be contextually a cause or an effect.

The present research study developed an operational uncertainty assessment composite score, which allows manufacturing industries to improve decision-making and help contextualise the configurations development. Thus, this approach takes into consideration the recommendation of Miller (2018) to blend quantitative and qualitative analyses as well as to Greckhamer et al. (2018) to build conceptually meaningful and empirically configurational theories.

Furthermore, this integrated approach also combined the PLS-SEM with fsQCA using the latent score as the input to fsQCA to avoid measurement error as alluded to by Rasoolimanesh et al. (2021). In line with other published work, the present study considered and employed thresholds for constituency and coverage to make sure the combination of conditions consistently predicts the outcome, and coverage assesses the extent to which the condition accounts for the outcome (Cangialosi, 2023; Papas &

Woodside, 2021; Sukhov et al., 2023). Several authors have indicated that the QCA is a valuable method for both theory building and testing (Oana & Schneider, 2021). Misangyi et al. (2017), supporting the earlier assertions of Greckhamer et al. (2013), argued that configuration analytical models are useful in theory building, theory extension and theory testing.

Using QCA in configurational theory systematically explores how different conditions interact to produce specific outcomes, offering a nuanced understanding of causality (Huang et al., 2024). Plugge and Nikou (2024) also support this view, arguing that configurational theory is integral to QCA as it facilitates the examination of complex causal relationships within systems.

Theories are developed to explain, predict, and comprehend phenomena, and they frequently push the boundaries of current understanding while expanding it (Paul et al., 2024; Shepherd & Suddaby, 2016). Theories offer the opportunity to view the same issue through different lenses depending on a particular research to determine which perspective it employs or adheres to, to construct an argument, define the background of the problem, and explain findings. This modified neo-configurational theoretical perspective adhere to the requirements of theory evaluation. Bacharach (1989) argued that falsifiability and utility should be used as the two criteria for evaluating the theory. Falsifiability evaluates whether the theory is constructed so that it is empirically refutable.

The present study provides evidence of falsifiability of this theoretical perspective. The critical components of a theory are indicators, constructs, and their relationships. A variable is also known as an observed unit empirically operationalised by the measurement. In contextualising this, Andrade (2021) posited that variables need to be operationalised, meaning they need to be defined in a manner that makes it possible to precisely measure those indicators. Such indicators depict the characteristics of the sample being analysed and fluctuate in value across the subjects within the sample (Calder et al., 2021). Similar to the explanation of Bacharach (1989), constructs are approximated units as they cannot be directly observed, while indicators were observed units derived from the survey involving personnel within manufacturing firms. This was empirically operationalised by measurement based on multiple methods. Guided by the boundaries, theory evaluation was performed using propositions. Good theory-building research methods are those that, like a theory itself, should specify the variables which

are also causal conditions, which are the operational uncertainty and its dimensions, Industry 4.0 and 5.0 technologies contribute and organisational learning with the outcome being sustained performance. Furthermore, as per the expectation by Bacharach (1989), there is a narrow focus to a specific topic on operational uncertainty and management using Industry 4.0 and 5.0 technologies benefit from these technologies showing clear, coherent, causal chain constructs, and offer six propositions (Wacker, 1998).

The indicators showed adequate variance for logical analysis and adequate reliability for stability. The *falsifiability of the constructs* was determined with convergence validity using AVE, discriminant validity with the Fornell-Larcker Criterion (1981), cross-loadings, and the Heterotrait-Monotrait criterion (HTMT) (Henseler et al., 2015). It was also conducted with predictive validity based on model's explanatory power, R^2 , effect size, f^2 and predictive relevance, Stone-Geisser's Q^2 (Hair et al., 2019).

Utility analysis determines whether the theory is useful, can be explained, and can predict the constructs, variables, and their linkages. In addition, utility evaluates whether the theory includes both the logical, which involves scope, and the empirical, which provides for explanation and prediction. This was confirmed in the present study with different methods, fuzzy-DEMATEL, PLS-SEM and QCA. The scope must ensure that the variables included in the theoretical system are sufficient but parsimonious (Bacharach, 1989). A confirmatory tetrad analysis can assist as it determines statistically whether a variable of the construct is best specified as reflective and a formative construct (Gudergan et al., 2008; Mtotywa & Kekana, 2023). The lower-construct in this study for operational uncertainty were reflective. This was confirmed with confirmatory tetrad analysis, with the tetrads not significantly different from zero, $\tau = 0$. The higher order construct was also confirmed and was found to be type 1, which supports a reflective-reflective model.

This modified neo-configurational theoretical perspective subscribes to the same foundational core tenets of causal asymmetry, conjunctural causation, equifinality (Meuer & Fiss, 2020). The new wave of research directly focuses on causal complexity (Misangyi et al., 2017), the neo-configurational perspective enables researchers to more adequately theorize and empirically examine causal complexity, and this expectation is similar to the modified neo-configuration theory.

Causal asymmetry was assumed testing the overall operational uncertainty model VI for presence and absence of the outcome. There was also conjunctural causation and evidence of equifinality with four solutions for a growing political tensions-based model and five solutions for energy stability and security-based model that would lead to sustained high performance. Based on structure and levels of operational uncertainty there is evidence of emergence tenets. This study postulates that there is a need for an additional tenet, an emergent core tenet in neo-configurational theory. This is as it was evident from the empirical analysis that operational certainty has multiple dimensions. To help understand this complex phenomenon through the interplay of multiple causal dimensions, rather than isolating single mechanisms. This tenet is mainly associated with the complexity theory (Turner & Baker, 2019). However, it explains that the emergence occurs when systems properties or levels of the complex firms are generated by agent self-organization. This is especially relevant as Yuan et al., (2023) explained that emergence and causality are interconnected, with new causality arising at higher levels of abstraction that cannot be attributed to individual properties alone. Critically, it is shown in these results that emergence occurs in firm transformation which is mainly not premeditated nor imposed by firm management as is the case with operational uncertainty. The emergent change, which is based on Industry 4.0 and 5.0 technologies and organisational learning, can generally arise in reaction to external environment alterations, which can be diverse (Gear et al., 2018). Emergent change enables firms to maintain adaptability and responsiveness to unplanned or unforeseen changes. Emergent change can be both gradual with continual modifications and/ or transformative over time. The initial model developed for the configurations of the study and analysed with the final framework provided in this chapter.

9.7 Chapter conclusion

The first research objective was to identify the components of the multi-dimensional construct of operational uncertainty. In this regard, the research identified nine such components at the external environmental level, at the industry level and at the individual firm level. These components of operational uncertainty were: growing geopolitical tension, policy and regulatory uncertainty, the cost of living-driven consumer behavioral change, pandemic turbulence, energy stability and security, leadership in sustainability and global responsibility, the entrenchment power of large firms, skills for future work within the industry, generational work behavior and ethics, and process capability and

variations. The second research objective was to determine the optimum operational uncertainty index. This uncertainty index was developed with 36 indicators, which were measured using a 5-point scale to determine the levels of uncertainty in decision-making. These levels of uncertainty ranged between predictable outcomes, alternative futures, range of futures and high uncertainty. The third research objective was to present the application of the operational uncertainty index in manufacturing industries. The study highlighted how this index can be applied to rank the most prevalent operational uncertainty factors for decision-making, to formulate a baseline for configurations in framework development and to act as a predictive factor for understanding the influence of operational uncertainty on the performance of a firm.

The second research objective investigated decomposing the capabilities of Industry 4.0 and 5.0 in manufacturing. In this study, Industry 4.0 and 5.0 provide several capabilities, which are scenario planning and future prediction, supply chain integration and collaboration, flexible production and mass customization, real-time system and process monitoring and response, root cause analysis and sustainable solutions, learning, talent development and upskilling, and protection ecosystem (human and systems). The third research objective assessed the possible impact pathways of the capabilities of Industry 4.0 and 5.0 technologies that can help manage operational uncertainty in manufacturing. The impact can involve supply chain disruptions, increased costs, market access restrictions, currency value fluctuations, changes in demand for goods, labour availability and productivity, quality of products, and knowledge management. As part of the future manufacturing industry agenda, these capabilities can be leveraged to form configurations for high-performance firms and other managing strategies to reduce and cope with operational uncertainty in manufacturing.

Chapter 10 Conclusions, Contributions and Recommendations

10.1 Introduction

Research is a systematic approach to solving an identified problem and gaining new knowledge in a particular area(s) of interest (Creswell & Creswell, 2017). Chapter 1 identified the current problem in the manufacturing sector, where operational uncertainty increases complexity, which puts pressure on a sector that is already struggling with growth and competitiveness. Mbengue et al. (2018) acknowledged that it is challenging to make accurate predictions regarding behaviour systems that are continuously influenced by an unpredictable environment. Despite this, there is a need to develop a theory-grounded solution to the prevailing problem to mitigate and, where possible, eliminate negative impacts on a firm. This would assist a manufacturing firm in developing effective strategies that contribute towards solving operational problems. More importantly, it contributes to the body of knowledge of operations management. There is a need for manufacturing firms to adapt to change as change is inevitable rather than to wait for a definitive final evolution of the change process. Likewise, the systems analysis in a firm should be so subtle as to detect change as it occurs and so obvious as to be appreciated by both management and staff. This ensures that all staff in a firm can work cohesively to counter the change in real time. Hence, this study is titled "Managing Operational Uncertainty in Manufacturing with Industry 4.0 and 5.0 Technologies: A Modified Neo-Configurational Perspective.

The research was conducted to holistically investigate three objectives aimed at developing a comprehensive understanding of operational uncertainty in manufacturing and to review and validate the capabilities of Industry 4.0 and 5.0 technologies in manufacturing. Using this information then, the focus was to formulate and analyse sustainable performance configurations (outcomes condition) with causal conditions from operational uncertainty and the usefulness of Industry 4.0 and 5.0 technologies and organisational learning.

Faced with this task, this research supports the assertions of Silva and Ferreira (2017), who noted that the complexity of theoretical concepts has made it challenging to research (operational) uncertainty and for a firm to respond appropriately to optimise performance designed to handle and mitigate the impact of sources of uncertainty. This is particularly within the context of influences from the external environment, and so the best approach is to deal with this challenge by attempting to contribute to a theory that would culminate in a practical framework. This research was guided by a systematic research design that provided a comprehensive plan for linking a conceptual research problem to relevant and attainable empirical research. The study acknowledges that there must be clarity of research design, paradigms, methodology and approaches to effectively address the research problem. This understanding is crucial for making decisions about data collection, analysis, interpretation, and reporting findings (Mkansi & Acheampong, 2012; Dawadi et al., 2021).

This last chapter summarises the key findings and contributions of the research. It also provides the strengths and limitations of the study, which are necessary to contextualise the findings. The latter part of this chapter provides the implications for industry and the policymakers and directions for future research. The future research direction recommendations are based on the limitations of the study and other emerging insights that were not fully investigated as they were not part of the scope of this current study. The last part of this chapter provides the study's concluding remarks.

10.2 Theoretical contribution

10.2.1 Integration of Industry 4.0 and 5.0 technologies in operations management and management in manufacturing

The exploration of Industry 4.0 and 5.0 technologies in operations management (OM) literature reveals significant insights into the field's evolution and emerging trends. Industry 4.0 technologies such as IoT, AI, and Big Data transform operations management by enabling smart, data-driven decision-making and real-time monitoring systems (Garrido et al., 2024). Integrating these Industry 4.0 and 5.0 digital technologies into operations management is reshaping traditional practices and highlighting new research opportunities. Thus, technologies such as AI, IoT, and big data, significantly impacts operations management by enhancing operational efficiency and decision-making processes. This trend is evident in the increasing number of publications focusing on

digital transformation in operations management, as highlighted by studies using both Scopus and Web of Science databases. Not only does the present study contribute toward integration, but it also expands on the management of the operational uncertainty dimensions with these Industry 4.0 and 5.0 technologies, thereby focussing on a new research opportunity.

10.2.2 Modified neo-configurational perspective

Several key factors drive the need for theory modification in operations management. These include the discipline's maturation, the integration of behavioural insights, and the necessity for rigorous and adaptable theoretical frameworks. As operations management evolves, there is a growing recognition of the limitations of existing theories and the need for frameworks that can accommodate new insights and methodologies. Operations management is a maturing field that necessitates extending theoretical frontiers through innovative research methods, such as qualitative analysis, to foster intellectual renewal and address emerging challenges (Narasimhan, 2014). Traditional models often assume rational behaviour but, importantly, incorporating behavioural and cognitive factors can enhance the relevance and applicability of operations management theories (Gino & Pisano, 2008). This is possible as other disciplines have successfully integrated behavioural insights, suggesting that operations management could benefit from similar adaptations to better reflect real-world complexities (Gino & Pisano, 2008). This transition is essential to address the dynamic nature of operations and the increasing complexity of global business environments. Walker et al. (2015) argued that most studies in operations management focused on theory testing rather than theory formation. Finding commonalities across disparate fields is crucial to theory-building since doing so raises the level of abstraction and potential impact of the research. As such, it is important to reflect on theories since they impact how research analyses and addresses operations management problems. This is essential in enhancing expertise in operations management while considering theoretical developments. A structured framework for theory adaptation, including stages such as problematisation and evaluation, can help balance academic and practical objectives, ensuring theories are robust and applicable.

Modifying theories allows operations management to remain relevant in rapidly changing business environments. By adapting theories to current socio-economic models,

businesses can better align their operations with contemporary challenges and opportunities. Furthermore, theory modifications can lead to more informed decision-making by incorporating diverse economic motives and stakeholder interests. This can result in a more comprehensive understanding of the operational environment and improved strategic planning.

The present study modifies the theory of neo-configurational theory, which was the second proposed by Misangyi et al. (2017). Misangyi et al. (2017, p.258) explained that "while the earlier wave of configurational research offered the intellectual roots for today's emergent neo-configurational perspective on management and organisations, the latter has its ontological and epistemological roots in Charles Ragin's introduction of QCA". The integration of fsQCA and other approaches and methods to strengthen the QCA to theory extension contributes towards theory. This, particularly in operations management, which uses the fsQCA, is still in its infancy despite being critical for real-world operations in sectors such as manufacturing.

10.3 Methodological contribution

The study has three methodological contributions. The two main contributions are the development of the operational uncertainty composite score index and the integration of Fuzzy-DEMATEL with PLS-SEM and fsQCA. The marginal contribution concerns the potential expansion of Lambert and Newman's (2023) 3-step process (Define—Operationalise—Confirm) for multi-dimensional constructs.

Improved research methodology is essential as it can also benefit theory improvement and practices. The Structural Equation Modelling (SEM) strengthens the link between theoretical and empirical research in operations management. The SEM confirms and extends existing theoretical frameworks, providing a robust tool for depicting causal relationships and advancing theory. Partial Least Squares-Structural Equation Modelling (PLS-SEM) plays a significant role in theory extensions by offering a flexible and robust approach to modelling complex relationships among variables (Hair et al., 2019). It is particularly useful in fields where theoretical models are still evolving, as it allows research to explore and validate new theoretical constructs and relationships. The PLS-SEM is adaptable to various research contexts, including information systems, engineering, and leisure research, making it a versatile tool for theory development across disciplines (Kono & Sato, 2023; Melo-Mariano & Plá, 2023). Critically, PLS-SEM

accommodates both formative and reflective measurement models, allowing research to model complex constructs often encountered in emerging theoretical frameworks (Hair et al., 2019; Kono & Sato, 2023). Melo-Mariano and Plá (2023) also advanced the ability of PLS-SEM to handle complex models, including its suitability for exploring new theoretical domains, such as Industry 4.0. This practical relevance is crucial for the evolution of theories that are not only academically sound but also practically viable.

While PLS-SEM offers numerous advantages, it is not without limitations. Critics point out issues such as biased estimates and the lack of measurement error estimation and model fit assessment tools (Kono & Sato, 2023). The integration of Partial Least Squares-Structural Equation Modelling (PLS-SEM) with fuzzy set Qualitative Comparative Analysis (fsQCA) can significantly contribute to the development of new theories by leveraging the strengths of both methodologies (Rasoolimanesh et al., 2021) and PLS-SEM is known for its ability to handle complex models and provide robust predictions, while fsQCA offers a configurational approach that can identify causal patterns across cases (Pappas & Woodside, 2021). Together, they can enhance theoretical insights and predictive accuracy in research (Rasoolimanesh et al., 2021).

10.3.1 Development of composite score – index

The study's contribution was the development of the operation uncertainty index, which is now known as the Manufacturing Operational Uncertainty Index (MOUI). The MOUI was conceptualised as a tool to quantify and manage the operational uncertainty that manufacturing businesses face in their operations. It impacts business decision-making by providing a structured way to determine the prevailing dimensions of operational uncertainty. In so doing, it provides levels of operational uncertainty, thus enabling the firm to make informed decisions. Table 10.1 provides the characteristics of MOUI.

The MOUI helps firms navigate these operational uncertainty dimensions by offering insights into potential risks and opportunities. Thus, it guides decision-makers in understanding and selecting the most suitable response with relevant preventive strategic actions to achieve their objectives for sustained performance.

Table 10.1: Characteristics of Manufacturing Operational Uncertainty Index (MOUI)

Characteristics	Description
Definition and Scope	Operational uncertainty refers to the external environment, industry or firm factors or dimensions that create complexity and unpredictability in manufacturing operations that affect decision-making.
Sources of Uncertainty* (dimensions)	• Geopolitical tension (GPT) • Policy and regulatory uncertainty (PRU) • Cost of living-driven consumer behavioural change (CLC) • Pandemic turbulence (PDT) • Energy stability and security (ESS) • Skills for future industrial work (SFW) • Entrenchment power of large firms (EPL), • Generational work behaviour and ethics (GWB) • Process capability and variations (PCV)
Model for multidimensionality	Reflective model (LOC)
Weight Estimates in development	Based on the importance of criteria, the inter-criteria correlation (CRITIC) method with Spearman correlation was used.
Type of index	Arithmetic Index

* - Other can be included or removed

Source: Author

10.3.2 Integrative approach to complex investigation and analysis

There is a dearth of studies on methodological integrations of symmetrical and asymmetrical methods. This study offers an integrative approach of fuzzy-DEMATEL with PLS-SEM and fsQCA. The inclusion of the optimising method fuzzy-DEMATEL by identifying the causal and effect conditions (López-Ospina et al., 2022; Yeh & Huang, 2014) was critical for root cause analysis, solution, and prioritisation. Understanding the causes over effects is critical in root cause analysis for effective problem-solving. This identifies the underlying causes of a problem rather than just addressing its symptoms,

which can lead to more sustainable and effective solutions. It is also important for continuous improvement, a daily need in a complex environment comprising very high competition, as is the case in manufacturing. This approach is essential in various fields, including manufacturing. This research provides a robust approach utilising a combination of symmetric and asymmetric approaches to make sure that the outcome moves beyond high value in the dependent variable but in several sufficient and necessary conditions. Additionally, it provides insights necessary to ensure robustness when checking to ensure the accuracy of the model by assessing the nonlinear effects, $PLS_{predict}$ in the PLS-SEM, and the predictive validity in the fsQCA findings. This study can contribute to the ongoing debate within QCA regarding which of its main solution types should be prioritised for substantive interpretation, arguing for an integrated approach to understanding these solutions (Haesebrouck, 2022).

10.3.3 Expansion of method for multi-dimensional construct

The study also suggests the increase in robustness of the 3-step process (Define - Operationalise-Confirm) by Lambert and Newman (2023). This is through additional analysis with the validation of the higher-order construct (HOC). The analysis in HOC examines the multiple relationships among various blocks of manifest variables. The criticality of the addition is that it is able to categorise the HOC from the four generic types of HOC models, of which, in this study, was type I (reflective-reflective model) (Crocetta et al., 2021).

10.4 Practical contributions – Management of operational uncertainty with Industry 4.0 and 5.0 technologies

In contemporary business environments, the focus of competition has shifted from the mere accumulation of resources to the active acquisition and application of knowledge within organisations. This is a recognition of the crucial role that knowledge and learning play in ensuring the survival and ongoing development of business firms (Tan & Olaore, 2022). Successful high-performing firms embrace priorities that best meet the conditions of the operating environment, especially stability and dynamism (Badri et al., 2000; de Waal, 2021). These firms emphasise the importance of accountability for achieving excellence and fostering continuous improvement. Within a plethora of strategies and practices, high-performance firms adopt competitive priorities and set up mechanisms to react to the forces in the operating environment. These firms adapt to the complexity of

their external environment because their organisations use environmental variables as sources for effective controls. Nsakanda (2021) posited that Africa must not overlook this revolution and should not be content with remaining stagnant while the rest of the world progresses. In the real world, relationships between variables are not always symmetrical. As such, a comprehensive understanding of the configuration is achieved by considering the interplay between its various dimensions and their relationship to the other elements within the configuration as a whole. Advanced data acquisition technologies, such as the Industrial Internet of Things and Digital Twins (Chikwendu et al., 2025), enhance the ability to perform detailed cause analysis, leading to better-informed decision-making.

10.5 Strengths and limitations of the research

This research has its strengths, and it also has its limitations. The strength of a study is crucial as it determines the reliability and validity of the findings, while the limitations provide context for interpreting results, guide future research, and help readers understand the scope and applicability of the study.

10.5.1 Strengths of the study

The research strength is a strong and relevant theoretical grounding, effective linkage of theory and methods, and the use of multiple methods of analysis with rigour in each method.

Theoretical grounding. The research is grounded on two relevant interrelated theories: complexity and configurational. Complexity theory was used as a grounding or contextualising theory, while configurational theory was used as the operationalising theory. Complexity theory generally emphasises dynamic interactions within systems and emergent properties (Leydesdorff, 2008), while configurational theory focuses on the specific arrangements or configurations of elements within a system that lead to particular outcomes (Iannacci & Kraus, 2022). Both theories offer valuable insights into the study of complex phenomena.

Linkage of Theory and Methods. The research effectively integrates theory and methodology. There is often a false division between theory and method that can hinder the development of comprehensive research designs. As a result, this separation can lead to a lack of problem-driven research and insufficient theory testing. The configurational

theory can be operationalised with qualitative comparative analysis (QCA) (Park & Mithas, 2020). QCA is a valuable method for both theory building and testing (Oana & Schneider, 2021; Misangyi et al. (2017).

Multiple methods of analysis with rigour in each method. This research strength is also its use of multi-methods to analyse the data to gain insight, increasing the research's robustness and rigour (Marquart, 2017). All the methods applied were relevant to the objective and proposition tested. More importantly, each method applied followed a robust procedure. Efforts were made to ensure relevant recent literature for advances in the methods to investigate the particular objective. This was both the application of the method and the reporting of the results. The importance of multi-analytical methods for data analysis lies in their ability to integrate diverse data sources and techniques to provide a comprehensive understanding of complex phenomena. These methods are crucial in fields where data are multi-dimensional and interrelated. Using a combination of analytical techniques, researchers can uncover patterns, relationships, and insights that would be difficult to discern using a single method. This approach improves the depth of analysis and the accuracy and reliability of the findings.

10.5.2 Limitations of the study

This research, like any other research, was not without limitations. In addition to the **methodological limitations**, which were highlighted in Chapter 5 related to the sampling bias generalisability, and resource intensity, the following study limitations are noteworthy:

Dimensions of the operational uncertainty. Despite the comprehensive inclusion of nine dimensions of operational uncertainty, these sources are not exhaustive as there can be others that are included and can exist, with this noted and denoted by (Other*) in each level (external environment, industry and firm).

Focus on Industry 4.0 and 5.0 technologies in manufacturing. The focus of the Industry 4.0 and 5.0 technologies in the manufacturing firms was whether they were in use or not in use. This means that the degree and variation of use were not included in the scope of the study, and this is important as potential limitations and an aspect to help contextualise the findings.

Industry 4.0 and 5.0 technologies were not exhaustive. The study acknowledges that there are other integrated Industry 4.0 and 5.0 technologies and/or individual technology extensions that form smart factories in manufacturing. These can potentially help to manage the operational uncertainty that was not investigated as they were not as highly used as the eight evaluated in this study. These include cyber-physical systems (CPS), digital twins, cobots (collaborative robots), and cloud computing. The extensions include technologies such as machine learning, which is part of artificial intelligence, and technologies such as the Internet of Industrial Things (IIOT) and Internet of Everything (IoE), which encompasses a range of connections, integrating people, processes, data, and things to create a seamless network (Ali et al., 2023)

10.6 Implications for Industry

The challenges in the manufacturing industries have been exacerbated by operating environmental turbulence and uncertainty that test their resolve for survival, growth and sustainability. The interaction of these factors generates uncertainty and volatility in the business environment. Due to the variety of patterns and events occurring across environmental sectors, firms are confronted with ambiguous situations that produce an even greater degree of uncertainty in the environment and pose latent dangers to their survival (Haque & Imran, 2016). This study has several implications for the industry and management of manufacturing firms.

10.6.1 Keep abreast of the prevailing operational uncertainty

Successful, high-performing firms embrace priorities that best meet the conditions of the operating environment, especially stability and dynamism (Badri et al., 2000; de Waal & de Waal, 2021). These firms exhibit and emphasise the importance of accountability for achieving excellence and fostering continuous improvement. The concept of high performance is closely linked to long-term sustainability (de Waal, 2021). Within the plethora of strategies and practices, high-performance firms adopt competitive priorities and set up mechanisms to react to the forces they face within the operating environment. These firms can adapt to the complexity of their external environment because their organisations make use of environmental variables as sources for effective controls. For the firm to make relevant and current decisions and sustain high performance, it needs to keep abreast of the prevailing operational uncertainty. This is critical in this changing and increasingly complex operating environment. This is more so considering that this

complexity can come from the external environment, industry, and the internal environment within the firm.

10.6.2 Increase technology adoption trajectory and effective use

There is a critical need for a business firm to continue in this trajectory, as highlighted in the PwC report on the increasing adoption of Industry 4.0 and 5.0 technologies. Granted, they might not always be easy due to barriers such as the level of required investment, inadequate skills, and infrastructure. Despite this, there is a need to continue adopting them as they provide the necessary options to mitigate the challenges of operational uncertainty.

10.6.3 Monitoring and evaluation of performance and learning

An approach to measuring the long-term impact of monitoring and assessment within the firm is crucial to morning the improvement or changes. A longitudinal study is one way to determine if an improvement method works, that is, if it helps improve organisational performance significantly and is long-lasting. The impact can be analysed using the difference-in-differences (DiD) method and those from the industry with similar structures, such as data envelopment analysis (DEA). The DiD method is frequently used for impact analysis and is commonly employed to assess the impact of a particular intervention involving the adoption of configurations propelled by technologies associated with Industry 4.0 and 5.0. This intervention aims to enhance performance during times of operational uncertainty. Figure 10.1 illustrates the expected impact of Industry 4.0 and 5.0 technologies intervention on a firm facing operational uncertainty.

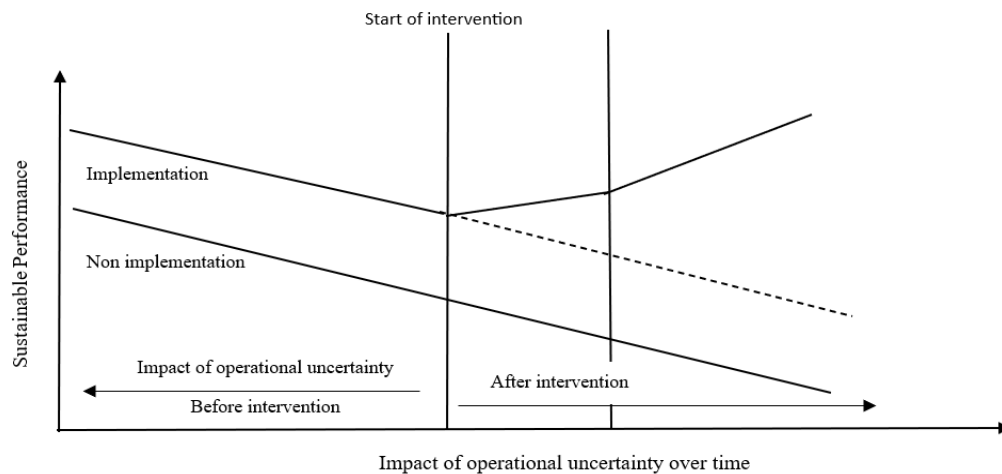


Figure 10.1: DiD illustration of the impact of uncertainty before and after intervention with Industry 4.0 and 5.0 technologies in the firm

Source: Authors' own, adapted from Mtotywa and Mtotywa (2022).

The DID method is generally implemented as the regression model's interaction term between time and treatment group dummy variables.

$$DID_j = \beta_0 + \beta_1 DM_j + \beta_2 IT_j + \beta_3 DM_j * IT_j + \varepsilon_j$$

Manufacturing decision-makers are constantly confronted with a substantial volume of reports and metrics utilised to assess manufacturing systems' effectiveness. Due to the varying and occasionally contradictory evaluations offered by metrics, manufacturing decision-makers encounter challenges in effectively monitoring and enhancing the overall performance of the manufacturing system (Jain et al., 2011; Shewell & Migiroy, 2016).

10.6.4 DEA as foundation for analysis of comparative performance

Data envelopment analysis (DEA) is used to evaluate and establish the efficiency of decision-making units (DMUs) that are comparable in terms of their products or services. Such DEA is a non-parametric technique for measuring efficiency. The analysis method described herein is a linear programming-based technique commonly employed to assess the relative performance of organisational units. This method proves particularly useful when multiple inputs and outputs pose challenges to making accurate comparisons. The process entails identifying units that utilise inputs to generate outputs in the most

efficient manner relative to one another. The DEA utilises this information to construct efficiency frontiers based on the available organisational units' data (Jain et al., 2011). The DEA provides an approach to measuring the long-term impact of monitoring and assessment within the firm and benchmarking the firm's technical efficiencies against the industry peers with similar DMUs.

In line with the early thinking of Ambrosini et al. (2009) on the configurational approach to the dynamic of firm-level knowledge, this research also argues that the Industry 4.0 and 5.0 technologies can, in part or as a collective, contribute to a fully-fledged-smart factory, and help managers to configure their factories. This allows them to manage operational uncertainty and help their firms with sustained performance, which will go a long way to improving the firm's competitive advantage and curb the diminishing size of the manufacturing sector in South Africa and other parts of the world, especially in developing countries and in Africa. Configurations demonstrate that the dimensions originate from a common foundation: knowledge. Therefore, when examined collectively, these elements exhibit interdependence and contribute to a more nuanced comprehension of the subject. This implies that while each configuration may exhibit distinct characteristics, they are comprehensible within the context of interconnected features (Ambrosini et al., 2009).

Accelerating the creation and accumulation of firm-level technological capabilities is necessary for digital transformation and is an essential precondition for developing countries to leverage the capabilities of Industry 4.0 and 5.0 (Peerally et al., 2022).

Business firms should involve the implementation of world-class practices to achieve superior firm performance relative to competitors (de Waal, 2021; de Waal & Kraaijveld, 2022). High-performing firms embrace priorities that best meet the conditions of the environment, particularly stability and dynamism (Badri et al., 2000; de Waal, 2021). These firms adopt competitive priorities, which accept their environment and set up the mechanism to react to the forces it exerts. Additionally, they adapt to the complexity of their external environment and make use of environmental variables as sources for effective management. The high performance is closely linked to long-term sustainability. It involves implementing world-class practices and achieving superior firm performance relative to competitors (de Waal, 2021).

This study was conducted in South Africa, but it is relevant to other settings, especially in BRICS+ and other African countries.

10.7 Implications for policymakers

This research has implications for policymakers in relation to growing geopolitical tensions, energy instability and operational insecurity. As sources of operational uncertainty, collaborative learning and advancement of Industry 4.0 and 5.0 have the capability to manage operational uncertainty.

10.7.1 Energy stability and security for the manufacturing sector

The research results showed that operational uncertainty due to energy instability and insecurity significantly influences sustained performance in manufacturing. Geopolitical tension was also central to influencing sustained performance in this operational uncertainty. The overall management of energy stability and security is mainly at a macro level, which means the government must respond. It is then important that the government have policies, plans, and strategies that will ensure good energy stability and security. Granted, over the past 6 months, there has been improved energy security with load shedding being suspended. However, there is a case in which energy stability and security are in place for the long term. Together with that, it must remain affordable as it is quite important, with manufacturing being one of the most energy-intensive sectors. Intervention from state-owned enterprise and government policies can improve this critical dimension, which, if left unchecked or when the problem creates uncertainty, negatively influences sustainable performance in a geopolitically tense environment. The government needs to be at the forefront of balancing and delicately managing this phenomenon as South Africa is affected by it and to avoid situations that have a ripple effect, as being seen in Germany, where part of the economic challenges are attributed to their position within the Ukraine/Russia war regarding both financing and access to effective energy.

10.7.2 Manage domino effects of growing geopolitical tensions

South Africa is in a position where it trades with the West and East and is at the forefront of BRICS+. While it has traded with the USA, there are implications for BRICS+ and also its foreign policy on the Russia/ Ukraine war and the Middle East War, especially Israel in Palestine. The government must manage and ensure a good, delicate balance that can

contribute to minimising the impact of these geopolitical tensions on the influence of the South African manufacturing sector. This is important as the manufacturing sector is intertwined with other countries either as part of a multinational source of raw material, which is influenced by supply chain disruptions or terms of trade, amongst others.

10.7.3 Collaborative learning and advancement

Collaborative learning and advancement of Industry 4.0 and 5.0 capabilities are needed to manage operational uncertainty. The South African government can continue to strengthen this collaboration and include topics related to managing operational uncertainty with Industry 4.0 and 5.0 technology in priority agendas for cross-learning research, as well as innovative solutions. This may be achieved through platforms such as the BRICS Business Council, where manufacturing is one of the nine working groups. BRICS Business Council (2023, p.2) explained their work that "over the past decade, the programme of work of the BBC has enabled trade facilitation, investment promotion, and knowledge exchange, thus promoting sustainable economic growth and enhanced competitiveness amongst the BRICS nations."

10.8 Directions for future research

The present study provides insights into guiding future research on operational uncertainty and its management with Industry 4.0 and 5.0 technologies. The following areas are recommended for future research:

In-depth focus on an operational uncertainty dimension. A recommended direction for future research is delving in detail on the operational uncertainty dimensions, exploring underlying sub-dimensions using both quantitative and qualitative methods. The qualitative methods are particularly adept at exploring the 'what', 'how', and 'why' questions, providing a deeper understanding of phenomena. Although qualitative research is not typically generalisable, it offers rich contextual insights (Tuckerman et al., 2020). Quantitative research focuses on measuring and comparing variables, which are often used to establish associations or causal relationships.

Level of use of Industry 4.0 and 5.0 technologies. This research focused on 'in use' or 'not in use' as a binary analysis. Research is recommended to be carried out to understand use levels. The level of use of technology is crucial because it provides a nuanced understanding of how technology is integrated and used within a firm. By focusing on

the level of use, firms can identify areas for improvement, optimise resource allocation, and enhance decision-making processes.

Barriers to the use of Industry 4.0 and 5.0 technologies. The importance of these technologies is evident in this research, and it is recommended that research be conducted to understand the barriers and their impact on implementation. Although these technologies offer significant advancements, addressing barriers is essential for successfully implementing and integrating Industry 4.0 and 5.0 technologies in manufacturing (Sharma et al., 2024).

Other Industry 4.0 and 5.0 technologies. The study was limited to the eight most common Industry 4.0 and 5.0 technologies in manufacturing. However, it would be beneficial to study operational uncertainty management with other integrated technologies. These include cyberphysical systems (CPS), digital twins, cobots (collaborative robots), and cloud computing.

Comparative analysis for managing operational uncertainty with Industry 4.0 and 5.0 technologies. Comparative analysis will offer a structured approach to identify trends, patterns, and insights by comparing data against benchmarks and between different countries. Research can be done to compare the management of operational uncertainty with technology. Thus, with BRICS+ partner countries such as China and India, this can be integral to further developments in this field. China has a dominant manufacturing sector and huge advances in technological capabilities (Asif et al., 2024); especially in artificial intelligence (Liu et al., 2022; Wang et al., 2023). India is also continuing to integrate Industry 4.0 and 5.0 into manufacturing, improving efficiency and competitiveness (Gupta et al., 2021). It is proposed that this study is longitudinal in nature. Longitudinal analysis in manufacturing is crucial for understanding and improving various aspects of production processes over time. It enables an examination of trends, the impact of technological investments, and the evolution of best practices, offering a comprehensive view of how manufacturing systems adapt and perform in changing environments. Investments in advanced manufacturing technologies have a time-lagged relationship with performance, suggesting that the benefits of such investments may not be immediately evident, but can result in significant improvements over time. The use of longitudinal data allows for a characterisation of the impact, providing valuable information for management, policy-making, and strategic planning.

10.9 Concluding remarks

The theoretical, literature, and empirical analysis outcomes of the present research study are essential since the recognition and dissemination of subjects within the field of operations management hold great significance for firms, which is contingent upon their sector of operation. Thus, this research offers valuable insights for academia, policymakers, the manufacturing sector, and management within the manufacturing firm. This understanding can aid in aligning their activities with the aim of effecting meaningful change in day-to-day business operations, allowing for more effective progress in the subject area, and promoting practical, real-world issue-solving.

Overall, it can be concluded that operational uncertainty is a multi-dimensional construct with dimensions in the external environment, industry, and firm levels. Critically this construct has been analytically confirmed to be flexible, and it does not break down when an indicator is added or removed in the lower-order construct or when the dimension is removed or replaced in the higher-order construct (operation uncertainty). The study also concluded that operational uncertainty is a norm in the manufacturing sector, as not all relevant information is already known to decision-makers. It is associated with a range of futures. This implies that due to the complexity of the variables (conditions) at play, it is impossible to divide these futures into a discrete and exhaustive set of possibilities, yet additional alternative futures are crucial to the decision. As such, the mechanisms that will bring about certain future conditions cannot be simply specified, making it impossible to calculate the precise probability of future events. It can further be concluded that Industry 4.0 and 5.0 technologies have the necessary capabilities to manage operational uncertainty and its prevailing dimensions. The research's theoretical and methodological contributions advance the modified neo-configurational perspective.

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List of Appendices

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Appendix A: Ethical clearance



Rhodes University Human Research Ethics Committee
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16 November 2023

Matolwandile Mtotywa

Email: Matolwandile.Mtitywa@ru.ac.za matolwandile.mtitywa@ru.ac.za

Review Reference: 2023-7527-8189

Dear Matolwandile Mtotywa

Title: Managing operational uncertainty in manufacturing with fourth and fifth industrial revolution technologies: A complexity-configurational perspective

Researcher: Matolwandile Mtotywa

Supervisor(s): Prof Tshidi Mohapeloa

This letter confirms that the above research proposal has been reviewed and **APPROVED** by the Rhodes University Human Research Ethics Committee (RU-HREC). Your Approval number is: 2023-7527-8189

Approval has been granted for 1 year. An annual progress report will be required in order to renew approval for an additional period. You will receive an email notifying you when the annual report is due.

Please ensure that the ethical standards committee is notified should any substantive change(s) be made, for whatever reason, during the research process. This includes changes in investigators. Please also ensure that a brief report is submitted to the ethics committee on the completion of the research. The purpose of this report is to indicate whether the research was conducted successfully, if any aspects could not be completed, or if any problems arose that the ethical standards committee should be aware of. If a thesis or dissertation arising from this research is submitted to the library's electronic theses and dissertations (ETD) repository, please notify the committee of the date of submission and/or any reference or cataloguing number allocated.

Sincerely,

Dr Janet Hayward

Chair: Rhodes University Human Research Ethics Committee, RU-HREC

cc: Ethics Coordinator

Appendix B Experts' assessment of operational uncertainty

1. Please indicate the sector within the manufacturing industry in which you experienced (you can choose more than one).

Sector	Mark (X)	Specify
Industry		
Consultancy		
Academia		
Policy makers/implementation		

Industry
Coke, petroleum, chemical products, rubber & plastic
Food & beverages
Transport equipment e.g. automotive
Metals, metal products, machinery & equipment
Other*

Based on Classification by Statistics South Africa (2023)

*Wood, wood products, paper, publishing & printing; Furniture & other manufacturing; Glass & other non-metallic mineral products; Electrical machinery & apparatus; Textiles & clothing; Telecommunication; Medical & optical equipment.

2. Please indicate years of experience in that sector(s) [Qualifier: Minimum – 5 years]

Sector	Mark (X) and a line detail of experience
5 – 10 years	
11 – 15 years	
16 – 25 years	
More than 25 years	

3. Please indicate your highest qualification

Sector	Mark (X) and name the qualification
Up to Matric	
Diploma	
Degree	
Postgraduate degree	

4. Please indicate your operating field

Sector	Mark (X)
Strategic / General management	
Production	
IT and/or technology	
Marketing and Sales	
Academia	
Others (please specify)	

5. Please indicate your role

Sector	Mark (X) and specify
Senior / Executive management	
Middle management	
Specialist	
Junior Management / Supervisor	
Lecturer / Senior Lecturer	
Associate Professor / Professor	

Section 1: Operational uncertainty

Please complete the table below using the code: 1- No influence 2 – Very low influence 3 –Low influence 4 – High influence 5 – Very high influence.

When completing, note that you do a pairwise determination of the row's influence on the column. For example, 4 means that the growing geopolitical tension has a high influence on policy and regulatory uncertainty (drop down).

	Growing geopolitical tension	Policy and regulatory uncertainty
Growing geopolitical tension		4
Policy and regulatory uncertainty		

	Growing geopolitical tension	Policy and regulatory uncertainty	Cost of living-driven consumer behavioural change	Pandemic turbulence e.g COVID-19	Operational uncertainty of energy stability and security	Operational uncertainty from generational work behaviour and ethics	Skills for future work	Entrenchment power of large firms	Process capability and variations
Growing geopolitical tension		Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Policy and regulatory uncertainty	Choose an item.		Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Cost of living-driven consumer behavioural change	Choose an item.	Choose an item.		Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Pandemic turbulence e.g COVID-19	Choose an item.	Choose an item.	Choose an item.		Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Operational uncertainty of energy stability and security	Choose an item.	Choose an item.	Choose an item.	Choose an item.		Choose an item.	Choose an item.	Choose an item.	Choose an item.
Operational uncertainty from generational work behaviour and ethics	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.		Choose an item.	Choose an item.	Choose an item.
Skills for future work	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.		Choose an item.	Choose an item.
Entrenchment power of large firms	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.		Choose an item.
Process capability and variations	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	

Section 2: Impact of operational uncertainty in manufacturing

Please complete the table below using the code: 1- Insignificant (Minimal impact) 2 – Minor (Short-term impact) 3 –Moderate (Significant impact) 4 – Major (Major short-term impact) 5 – Severe (Major long-term impact). (drop down)

	Supply chain disruption	Increase the cost of production	Market access restriction	Fluctuation of currency value	Change in customer demand	Restricted labour availability & decreased productivity	Quality of the product negatively affected	Compromise knowledge management
Growing geopolitical tension	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Policy and regulatory uncertainty	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Cost of living-driven consumer behavioural change	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Pandemic turbulence e.g. COVID-19	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Operational uncertainty of energy stability and security	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Operational uncertainty from generational work behaviour and ethics	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Skills for future work	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Entrenchment power of large firms	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Process capability and variations	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.

Section 3: Technologies (fourth and fifth industrial revolution technologies)

Please complete this table to determine the best technology for the required manufacturing capability (drop down). Note: Capabilities; 0 = incapable; 1 = Partially capable; 2 = Fully capable

Capabilities	Internet of Things (IoT) and/or Enhanced Connectivity	Artificial Intelligence and/or Machine Learning	Advanced Robotics - Autonomous Robots and Robotic System	Blockchain	Augmented and/or Virtual Reality	Additive manufacturing (3D printing)	Quantum Computing
Demand Forecasting	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Customer Feedback and Market Analysis	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Scenario planning	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Real-time tracking of shipments	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Supply chain and Inventory management and Optimisation	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Resource management	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Design, Product Development and Customisation	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Material Handling and Transportation	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Predictive maintenance (Maintenance and Repairs)	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Asset tracking and management (Process and Product Optimisation)	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Remote machine monitoring and control	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Inspection and quality control/quality control and defects detection	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Real-time monitoring and decision making	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Energy management	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Complex-problem solving	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Risk analysis	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Training and Skills Development	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Safety monitoring	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Environmental monitoring	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
Cybersecurity and counterfeit prevention	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.

Appendix C Firm Survey

Managing operational uncertainty in manufacturing with Fourth and Fifth Industrial Revolution technologies: A complexity-configurational perspective

Dear Respondent

My name is Matolwandile Mtotywa, a PhD candidate at Rhodes Business School. I request 20 -25 minutes of your time to complete this survey. The purpose of the study is to develop and validate a framework for identifying operational uncertainties and effective management configurations in manufacturing industries with fourth- and fifth-industrial revolution technologies.

If you have any enquiries during the participation in the survey, please do not hesitate to contact me or my supervisor, Prof Tshidi Mohapeloa, or if you notice any unethical conduct in this study, do not hesitate to contact and report it to the research ethics committee at Rhodes University.

Matolwandile Mtotywa: Email – Matolwandile.mtotywa@ru.ac.za

Prof. Tshidi Mohapeloa: Email – t.mohapeloa@ru.ac.za

Dr. Janet Hayward (Human Ethics REC: Chairperson and Ethics Coordinator)
- Janet.Hayward@ru.ac.za

In participating in the study, please note the following ethical considerations and your rights by reading the attached informed consent, do you consent to participate?
(conditional formatting survey – in case of “No”, thank the respondents and the survey ends).

Yes	
No	

The survey comprises five sections, and please complete all of them.

Section 1: Demographic information

1. Please indicate with a mark (X) the South African province where your manufacturing firm operates.

Province	Mark (X)
Eastern Cape	
Free State	
Gauteng	
KwaZulu-Natal	
Limpopo	
Mpumalanga	
North West	
Northern Cape	
Western Cape	

2. Please indicate the sector within the manufacturing industry in which you experienced in (you can chose more than one).

Sector	Mark (X)
Coke, petroleum, chemical products, rubber & plastic	
Food & beverages	
Transport equipment	
Metals, metal products, machinery & equipment	
Other*	

Based on Classification by Statistics South Africa (2023)

*Wood, wood products, paper, publishing & printing; Furniture & other manufacturing; Glass & other non-metallic mineral products; Electrical machinery & apparatus; Textiles& clothing; Telecommunication; Medical & optical equipment.

3. Please indicate the size of your firm, based on the annual turnover (revenue).

	Annual turnover**	Mark (X)
Micro	Turnover < R35 000 000	
Small	R35 million < turnover < R91 million	
Medium	R91 million < turnover < R357 million	
Large	More than R357 million	

***Based on the Department of Trade Industry and Competition's (DTIC) 2003 cut-off points, which are adjusted by a factor of 7 by Statistics South Africa (2023) for the size group cut-off points*

4. Please indicate the number of employees in your firm.

Staff complement	Mark (X)
1-10	
11- 50	
51 – 250	
251 – 1000	
More than 1000	

Section 2: Operational uncertainty

Please complete this section. Please select that best reflect the impact of the operational uncertainty in your firm. Agree = SD, Disagree = D, Neither disagree nor agree = N, Agree = A, Strongly agree = SA.

In each statement, there are four items read all four of them and sum those that impacts your firm and score from 0 to 4. If only one the score is 1, if all four of them, the score will be four. Following this, please highlight the one with highest impact from the drop-down menu. E.g. Availability of upgrading equipment or spare parts for existing imported equipment.

	SD	D	N	A	SA
1. Process capability and variations have a negative impact on the manufacturing operations as a result:					
The process throughput is inconsistent, indicating variation in production processes.					
The scrap and rework in manufacturing are higher than acceptable levels (higher than 5%).					
The firm does not leverage process capabilities to improve the design or processing of products.					
The firm does not achieve an overall equipment efficiency (OEE) at world-class levels of 85% or greater.					
2. Policy and regulatory uncertainty has resulted in a negative impact on the firm's manufacturing operations due to:					
Volatility in corporate tax.					
Increased red tape and higher cost of borrowing and attracting investors					
Increased cost associated with safety, health, and environmental aspects management in the workplace					
Constant changes in by-laws.					
3. Cost of living-driven consumer behavioural change has resulted in a negative impact on the firm's operations due to:					
Decrease in sales because of affordability challenge by the customers.					

Changes in customer preferences of pack size and number of quantities because of increased cost of living					
The firm products now being categorised as 'wants' and no longer 'needs'					
The firm products being regarded as unaffordable, with customers preferring cost-effective substitutes.					
4. Pandemic turbulence such as COVID-19 has resulted in:					
Increased costs of psychosocial support needed by staff.					
Fears remaining concerning job security in the firm due to struggles that occurred since COVID-19.					
Decrease in team interaction and diminishing natural bonding such as handshaking or hugging from staff members.					
Decrease in benefits structures such as study aid and performance rewards in the firm, with the firm attempting to save costs in response to turbulence caused by the COVID-19 pandemic.					
5. Operational uncertainty of energy stability and security has impacted the firm's manufacturing operations, as such:					
There is a lack of energy stability which creates chaos within the operations of the firm.					
The firm struggles to meet customers' delivery targets due to electricity disruptions.					
The firm product quality is negatively affected by electricity supply disruptions.					
The firm is losing market share and retrenching staff due to the impact of load-shedding.					
6. Operational uncertainty from generational work behaviour and ethics has an impact on the firm because:					
The firm's multi-generational workforce creates uncertainty in firm's culture and firm purpose.					
There is a conflict regarding the way of work amongst the different generations in the firm.					
Younger generation (Generation Y and Millennials) requires a flexible work environment compared to older generations (Generation X and older).					
The younger generation has high levels of attrition (resignations/ change jobs), resulting in continuous knowledge loss in the firm.					
7. Skills for future work are impacting the manufacturing operation because:					
The firm has not incorporated skills for the future such as critical thinking, problem solving, data analytics in the training and development of staff.					
The staff does not have the skills required for technological changes.					
Sensemaking (deconstructing and deciphering valuable knowledge from existing information and extracting unique insights) is not continuously developed in the firm.					
Virtual collaboration is not the norm in the firm.					
8. The entrenched power of large firms is impacting the firm operations because:					

Industry-dominant firms engage in unfair business practices to the detriment of the firm.					
Industry-dominant firms set the rules and dictate participation in the value chain.					
Due to insufficient economies of scale, the firm suffers from reduced productivity and product quality.					
Product marketing in the firm suffers due to lack of financial advantage or resources for marketing and sales.					
9. Growing geopolitical tension creates problems in the firm's manufacturing operations and has resulted in:					
Rising input (raw or semi-processed material) prices.					
Poor availability of upgrading equipment or spare parts for existing imported equipment.					
Longer turn-around time for maintenance and support of imported equipment.					
Increased costs of importing involving customs, tariffs, and other import duties					

Section 3: Technologies (fourth and fifth industrial revolution technologies)

Please indicate, with an X, the technologies that are in use in your firm.

Technologies	Mark (X)
Internet of Things (IoT) and/or Enhanced Connectivity	
Artificial Intelligence and/or Machine Learning	
Big Data Analytics	
Advanced Robotics - Autonomous Robots and Robotic System	
Blockchain	
Augmented and/or Virtual Reality	
Additive manufacturing (3D printing)	
Quantum Computing	
Others (Please specify)	

Please complete this section. In our firm, we use technology that is capable of the following:

Strongly disagree = SD, Disagree = D, Neither disagree nor agree = N, Agree = A, Strongly agree = SA.

Capabilities	SD	D	N	A	SA
Demand Forecasting					
Customer Feedback and Market Analysis					
Scenario planning					
Real-time tracking of shipments					
Supply chain and Inventory management and Optimisation					
Resource management					
Design, Product Development and Customisation					
Material Handling and Transportation					
Predictive maintenance (Maintenance and Repairs)					
Asset tracking and management (Process and Product Optimisation)					
Remote machine monitoring and control					
Inspection and quality control/quality control and defects detection					
Real-time monitoring and decision making					
Energy management					
Complex-problem solving					
Risk analysis					
Training and Skills Development					
Safety monitoring					
Environmental monitoring					
Cybersecurity and counterfeit prevention					

Section 4: Organisational learning

Please complete this section, identifying the levels of agreement with the following statements.

Strongly disagree = SD, Disagree = D, Neither disagree nor agree = N, Agree = A, Strongly agree = SA.

	SD	D	N	A	SA
There is a firm-wide established and managed technology-driven innovation culture.					
Firm personnel, including management and specialists, seek and take immediate corrective actions when our technology-driven processes are not functioning well.					
The team uses the firm's past experience to interpret the feedback on our technology-driven processes.					

In our firm, before taking action, we identify the root causes if there is a problem with our technological-driven processes.					
There is integrated learning in our technology-driven business process.					
There is an ecosystem and platforms for learning to enable the employees to maximize the use of installed technologies in our manufacturing processes.					
There is cross-learning and open knowledge sharing to ensure all relevant personnel can optimise the use of our manufacturing technology.					
Not only do we seek prompt actions if there are issues with our technology-driven processes, but we also adjust the long-term strategy to ensure maximum use with high impact from our technology.					
We systematically record performance feedback from our technology-driven processes for future reference.					

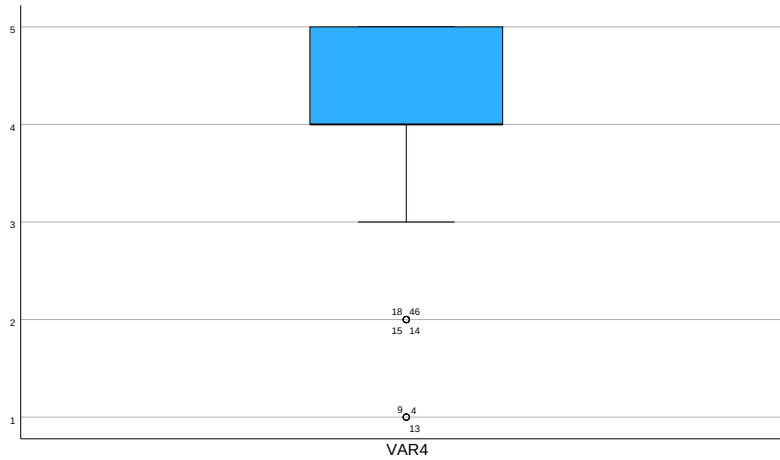
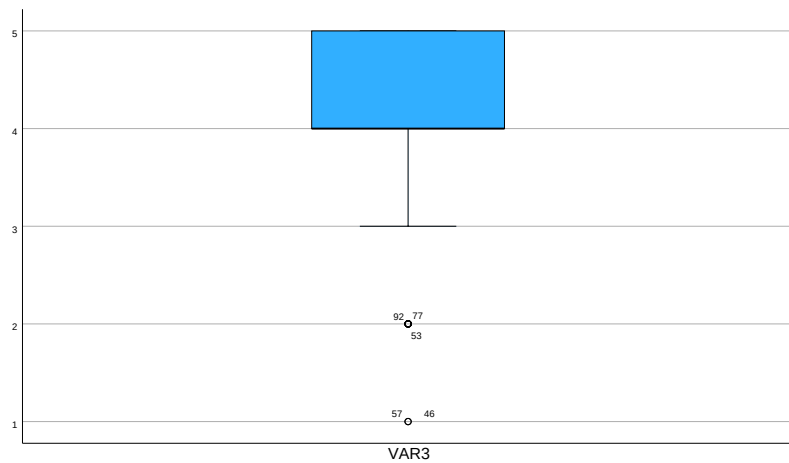
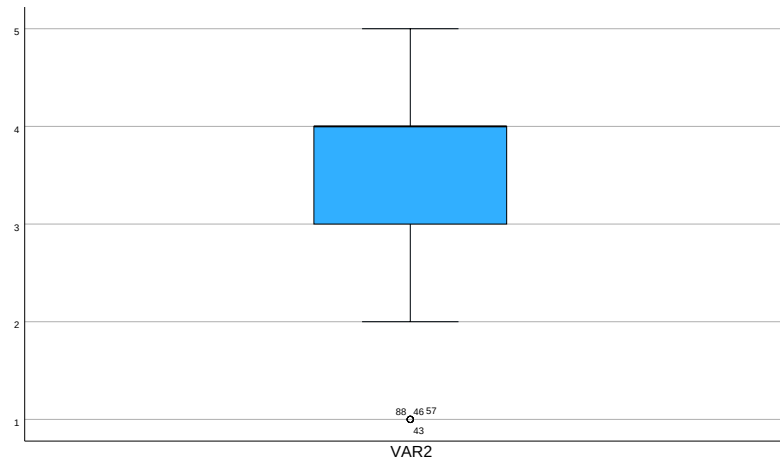
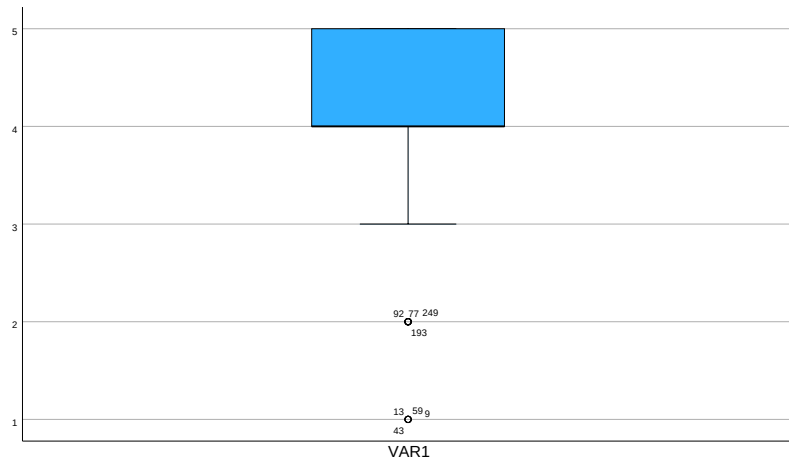
Section 5: Performance

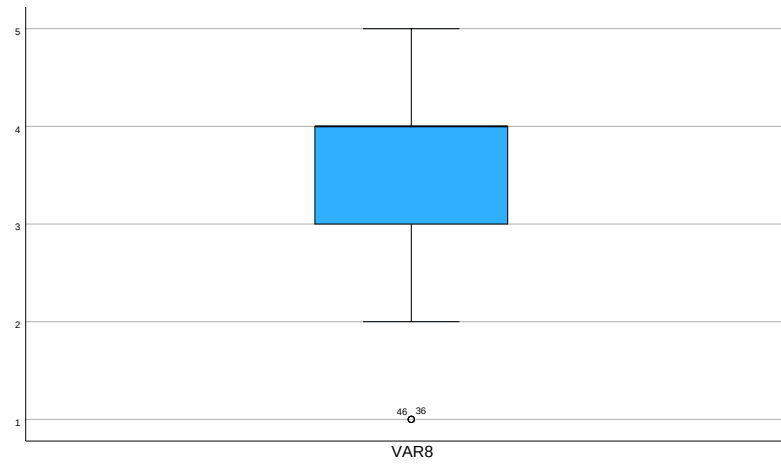
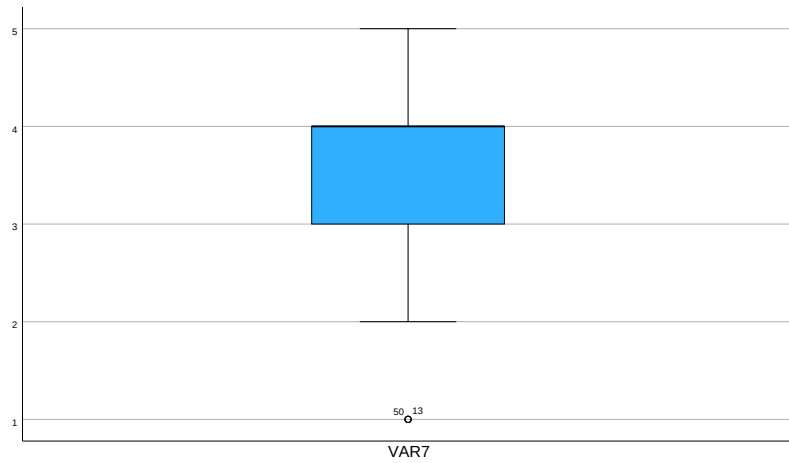
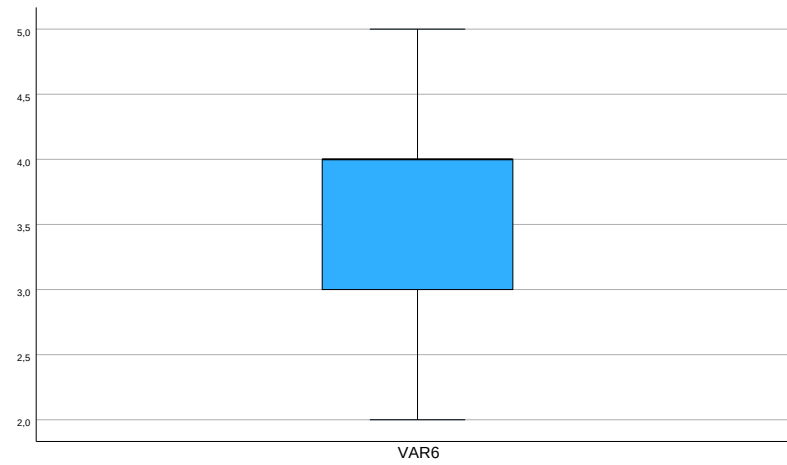
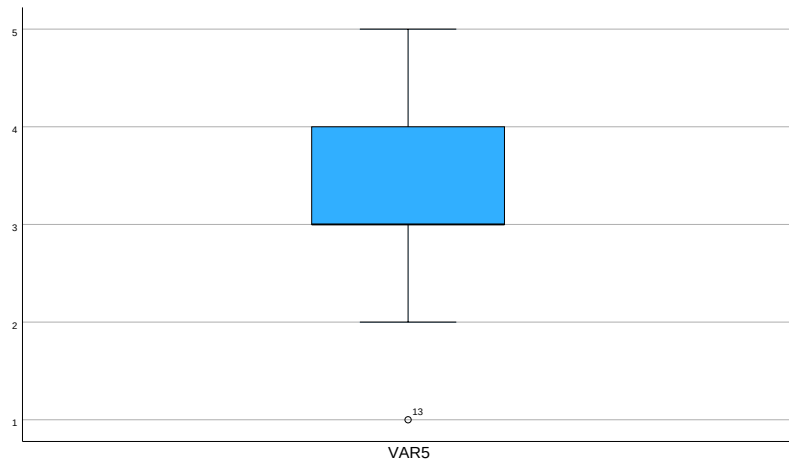
Please rank your firm's performance in the past 3 years based on the following, marking the relevant one with an X:

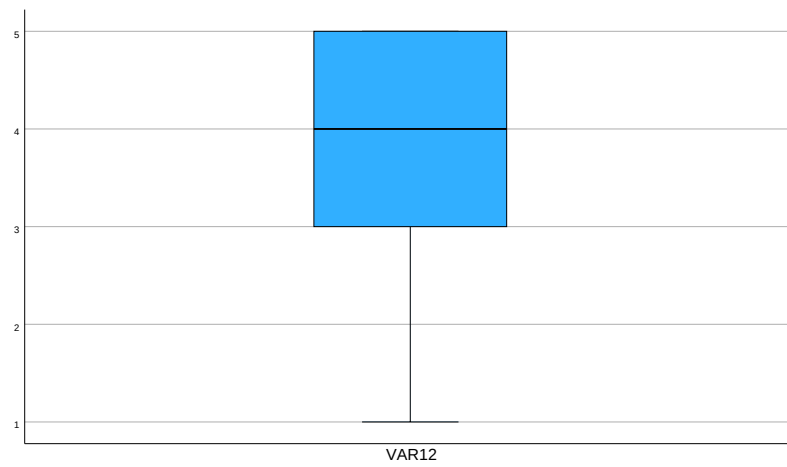
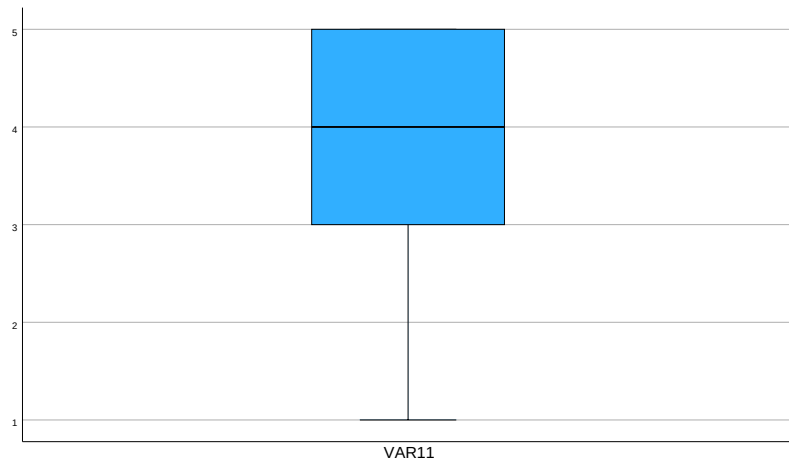
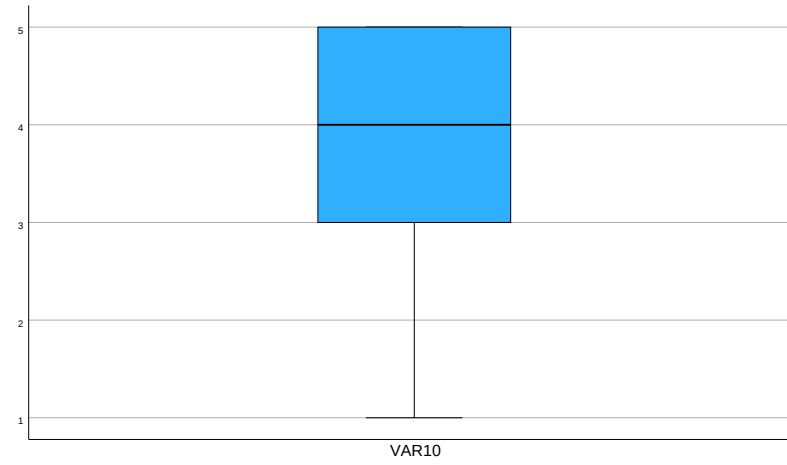
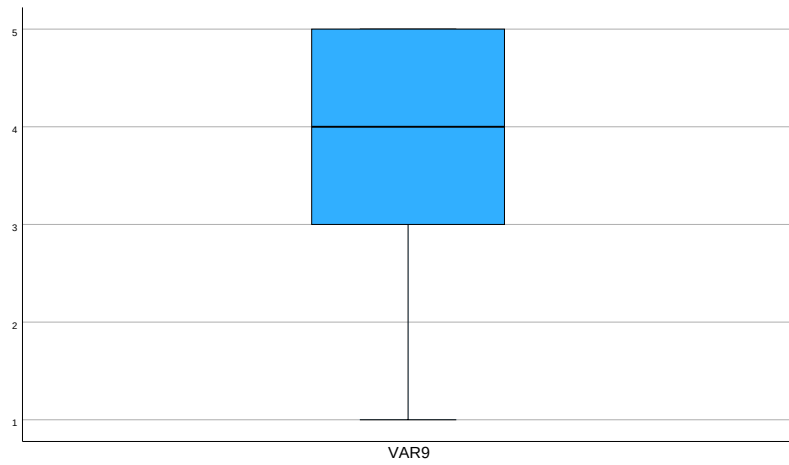
Pick a score from **1 – 10**, with a low score such as 1 indicating very negative outcomes, progress to 5 = no change, then towards **10** = very positive change.

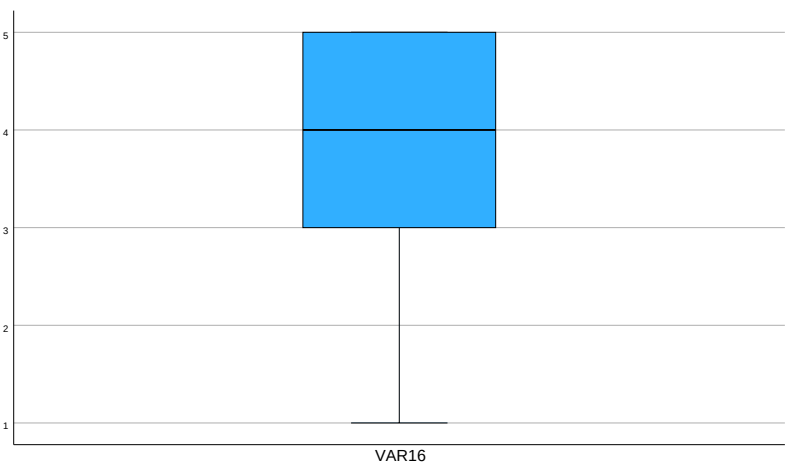
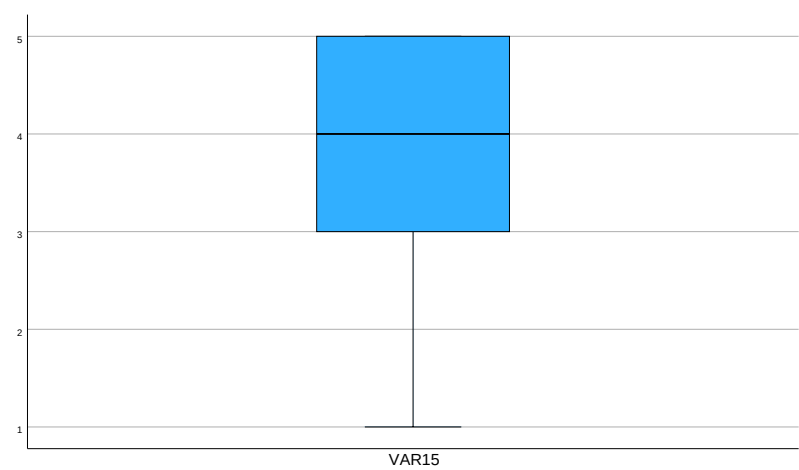
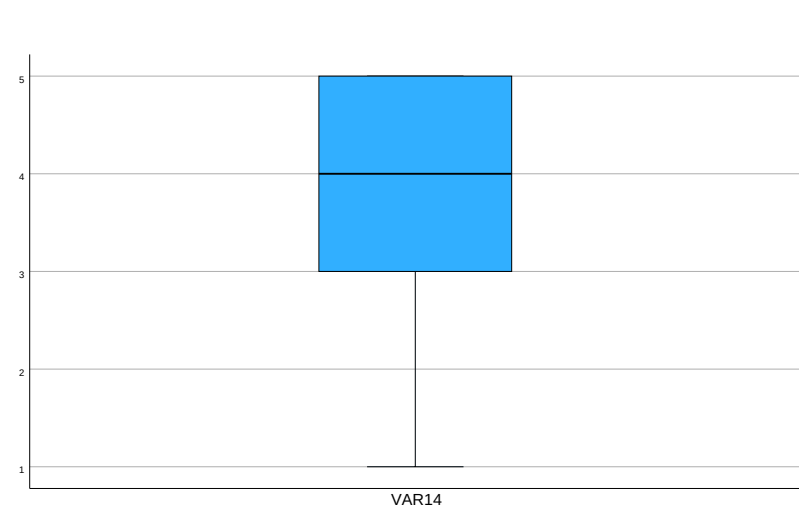
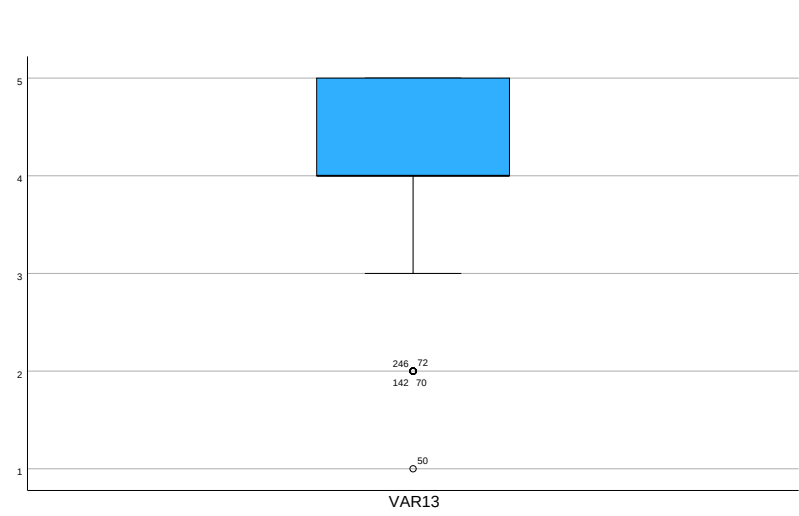
	1	2	3	4	5	6	7	8	9	10
The firm's profitability has been increasing for the past three years.										
The firm's overall process efficiency has improved over the past three years.										
Implementing sustainable practices in the past three years has yielded positive, measurable outcomes in the firm.										

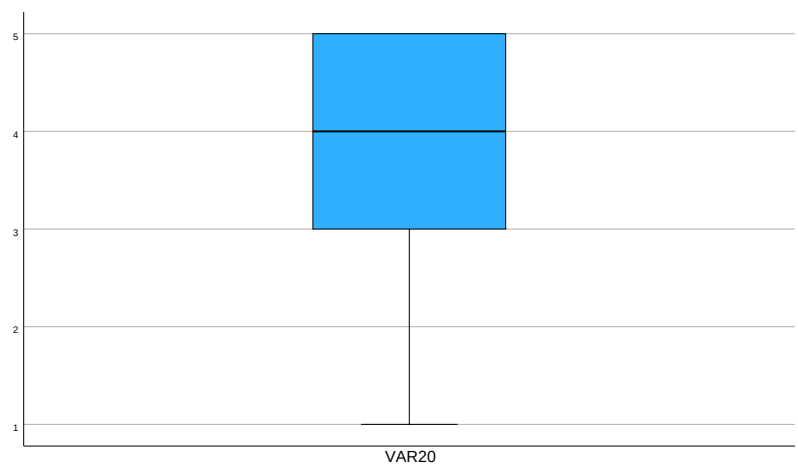
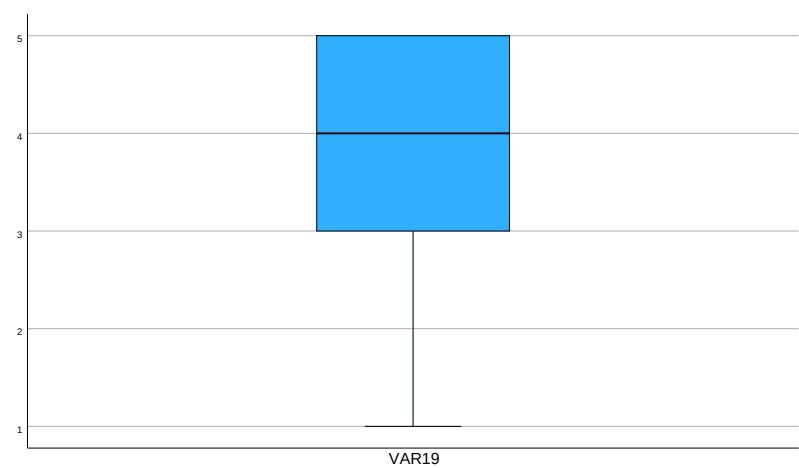
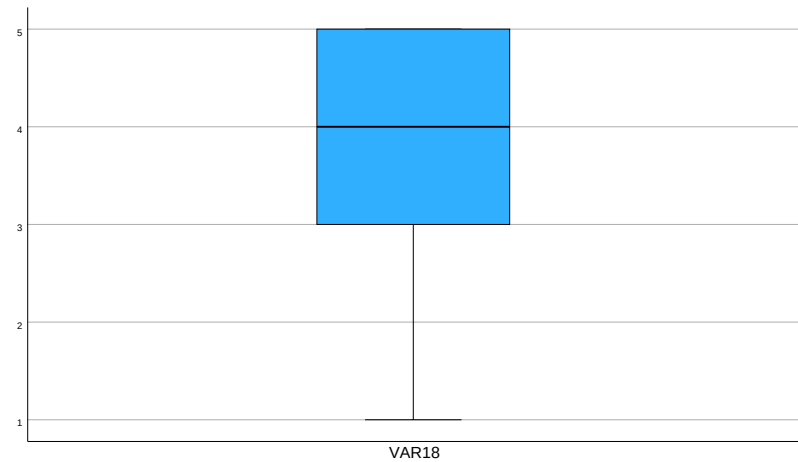
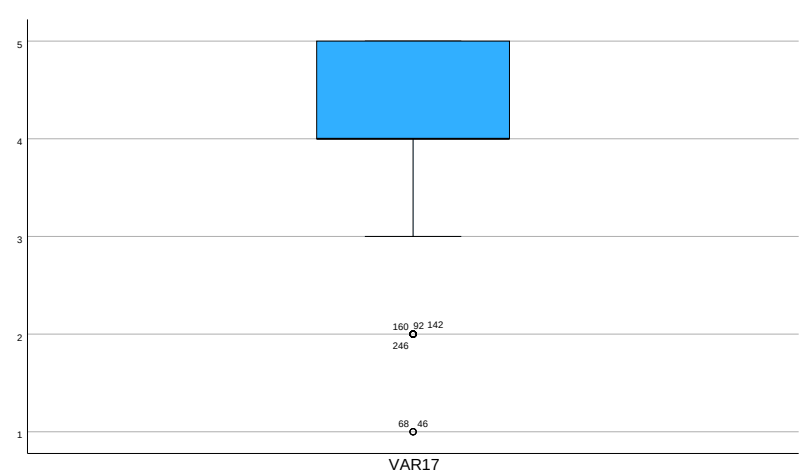
Appendix D Extreme outlier analysis with boxplot

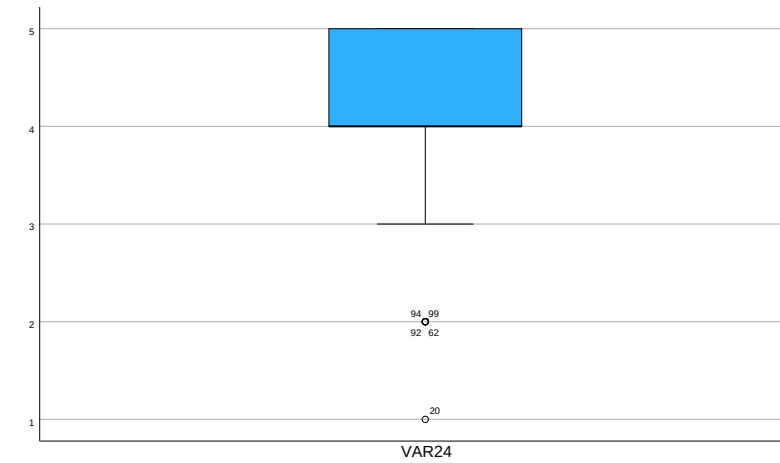
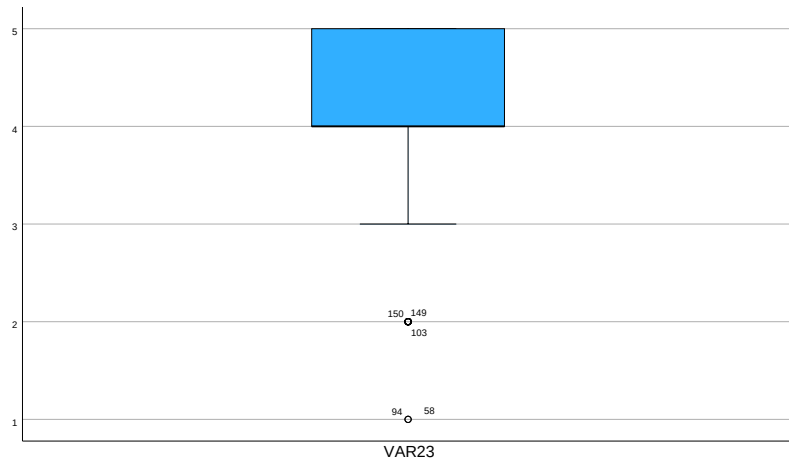
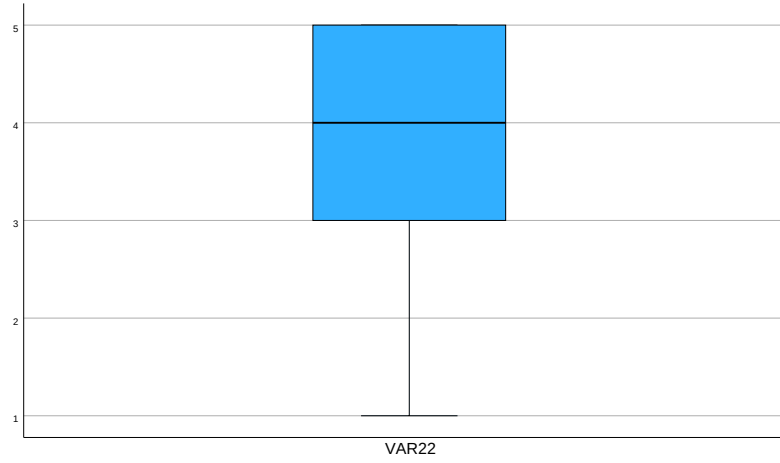
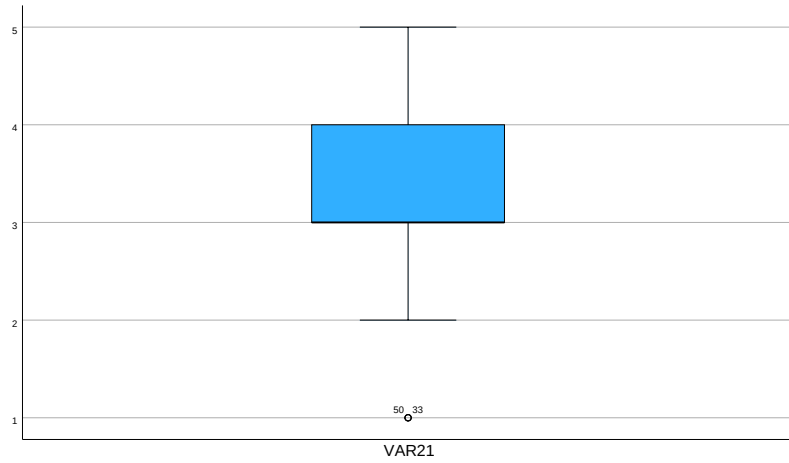


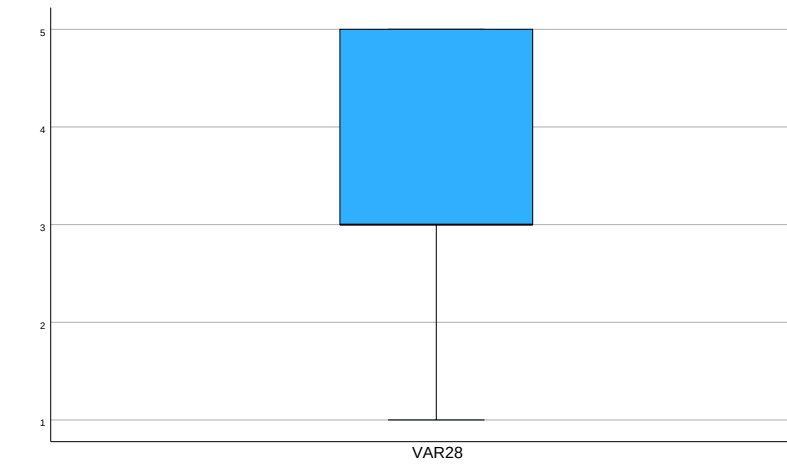
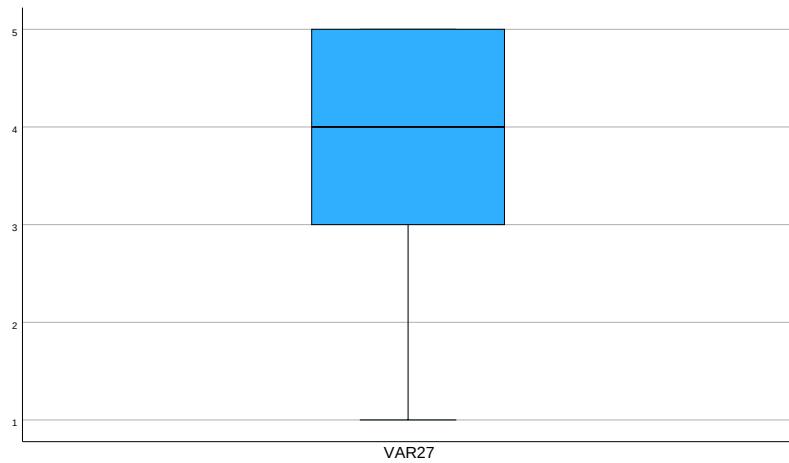
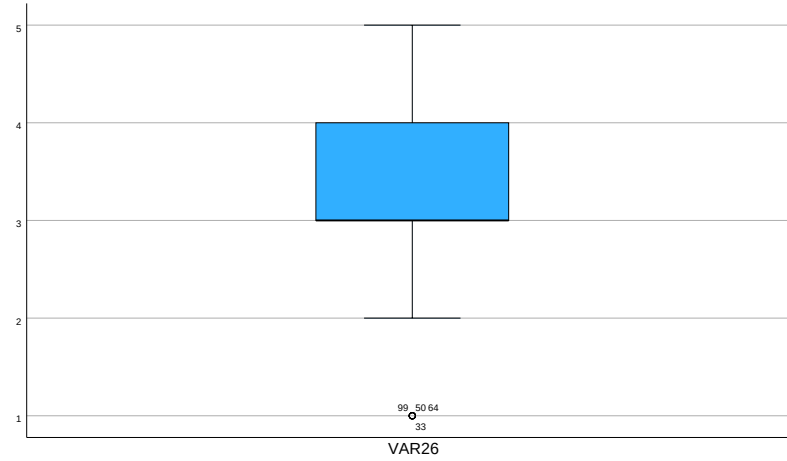
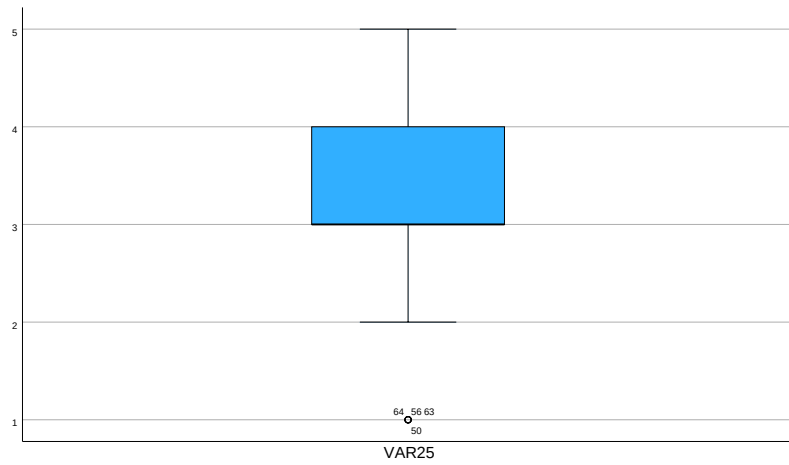


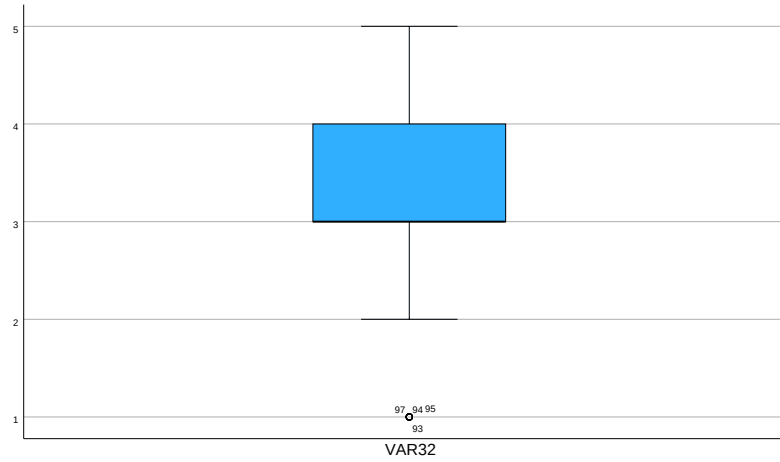
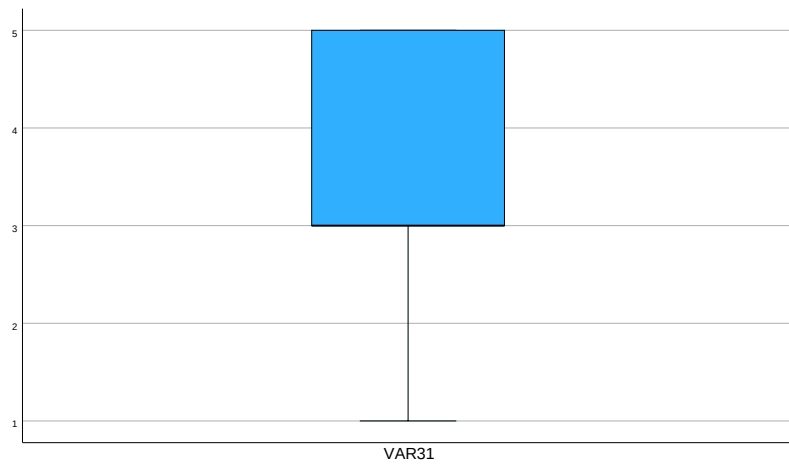
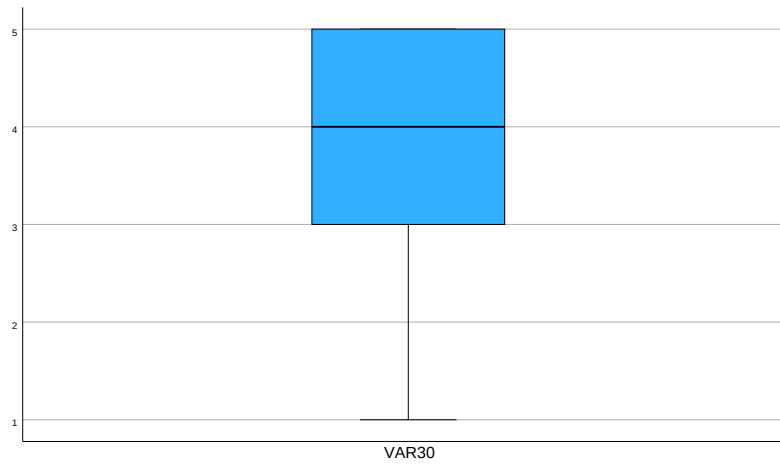
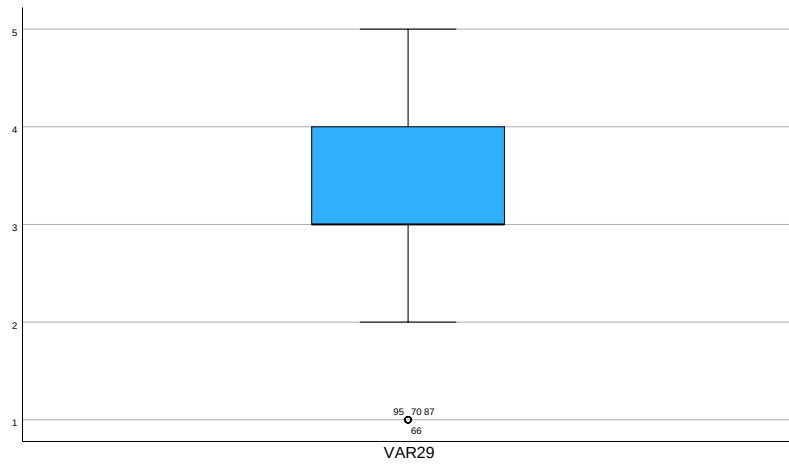


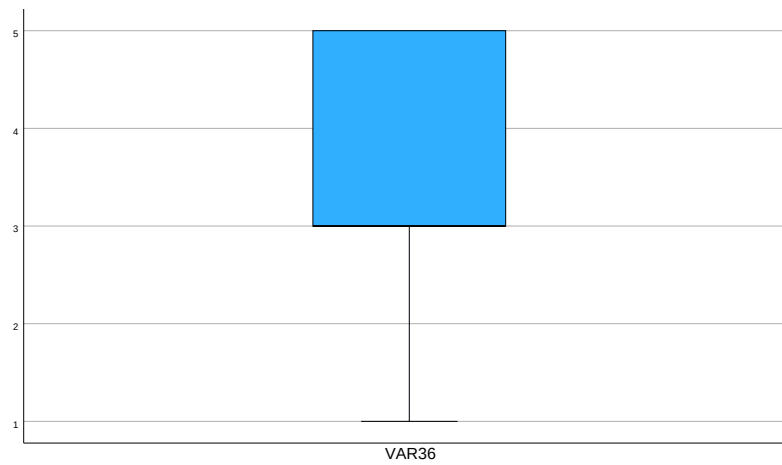
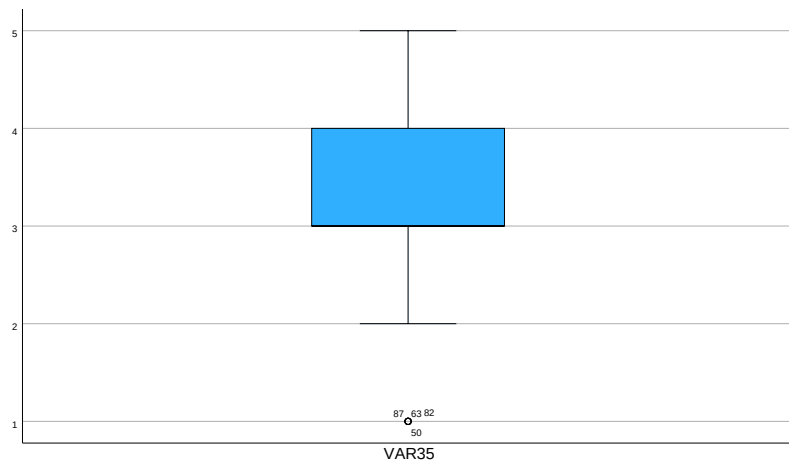
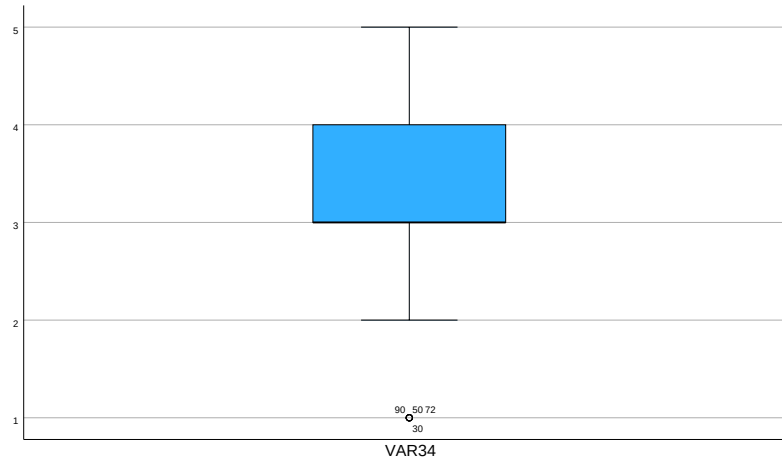
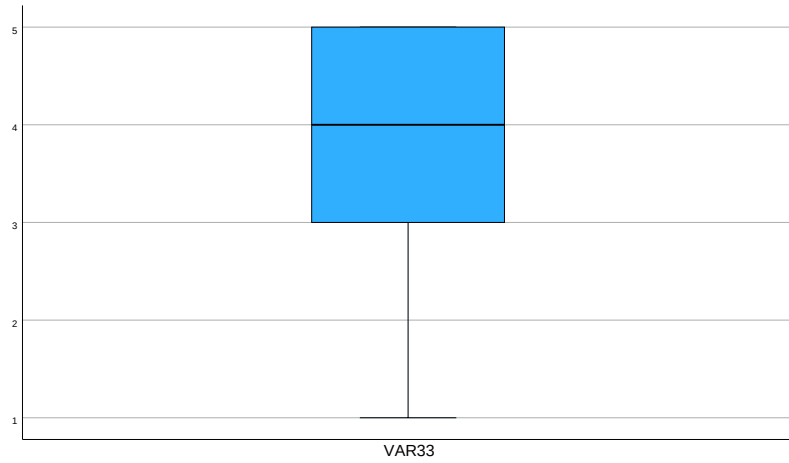


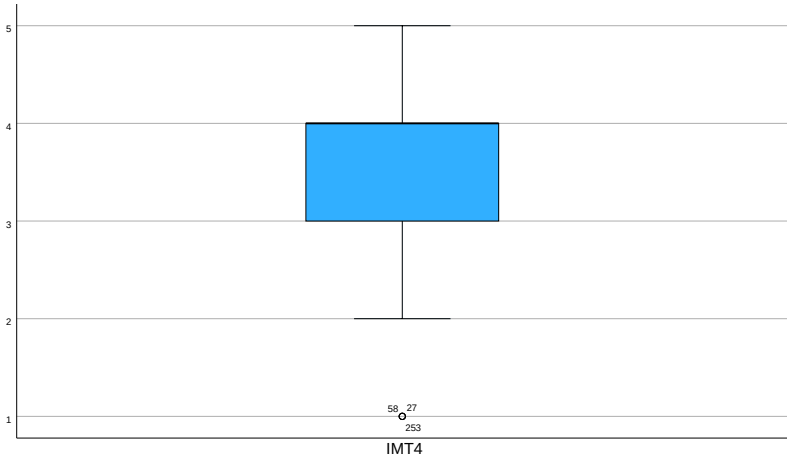
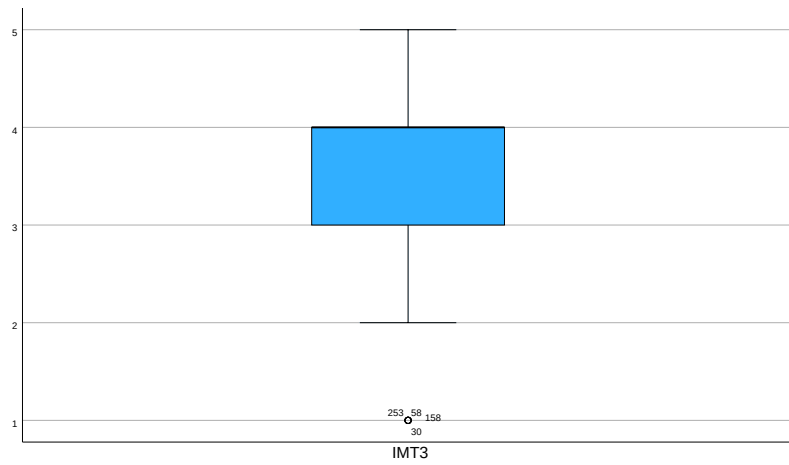
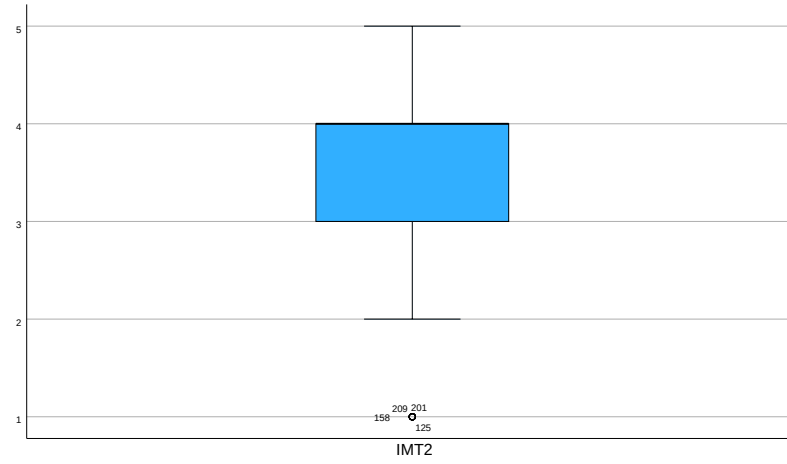
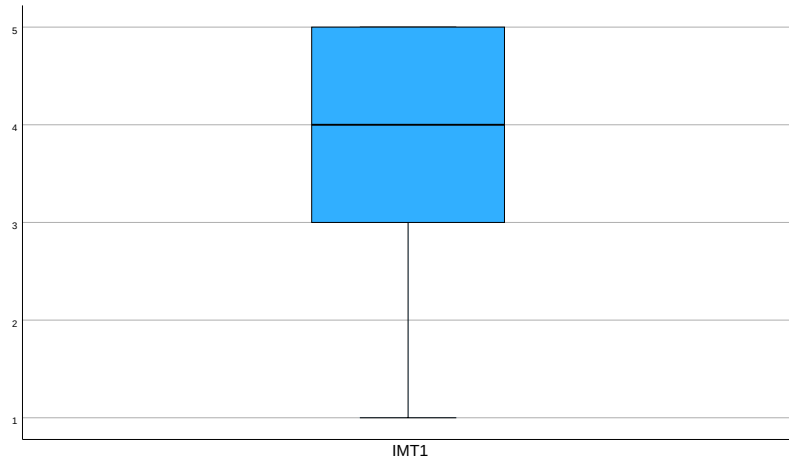


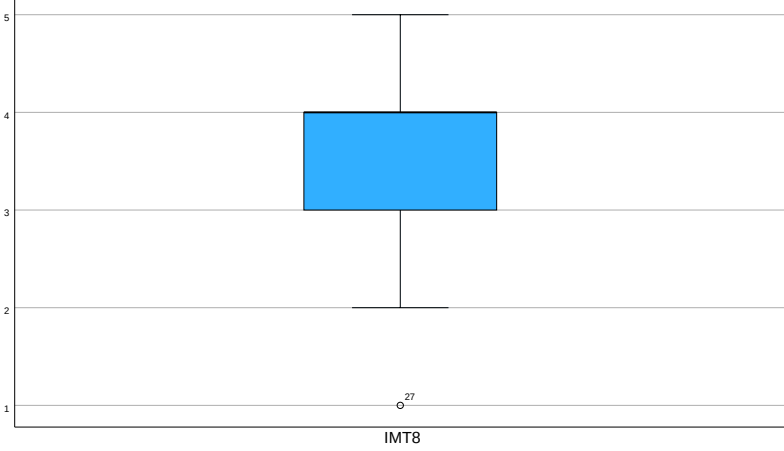
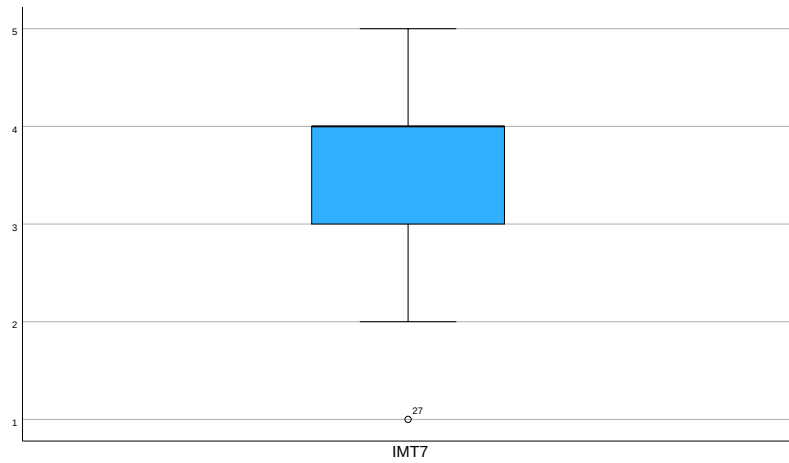
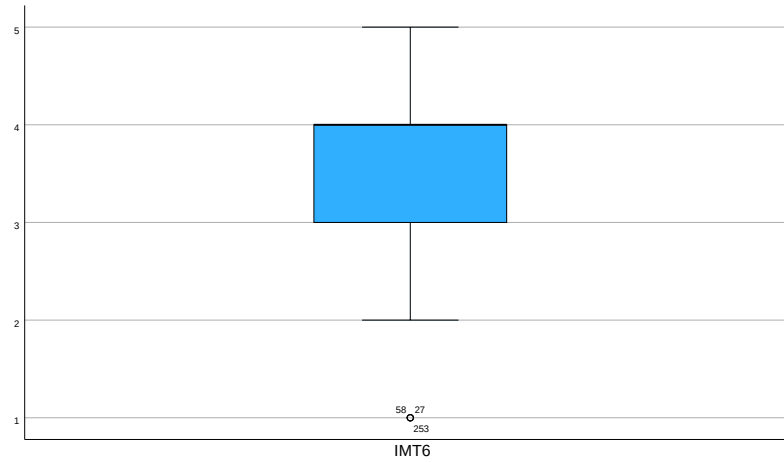
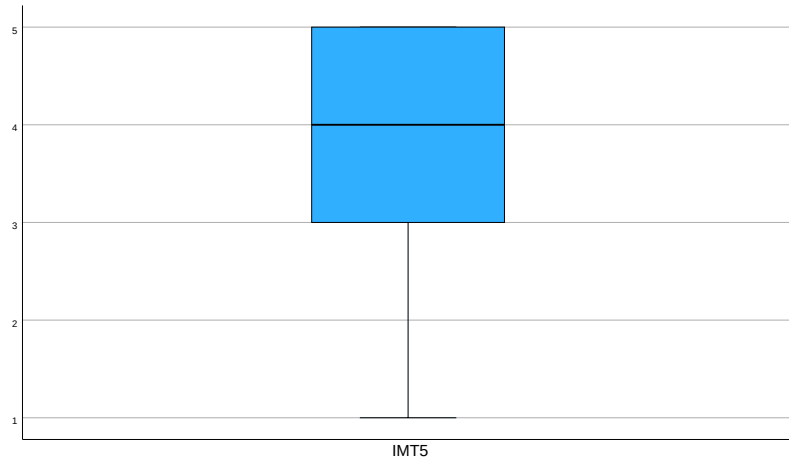


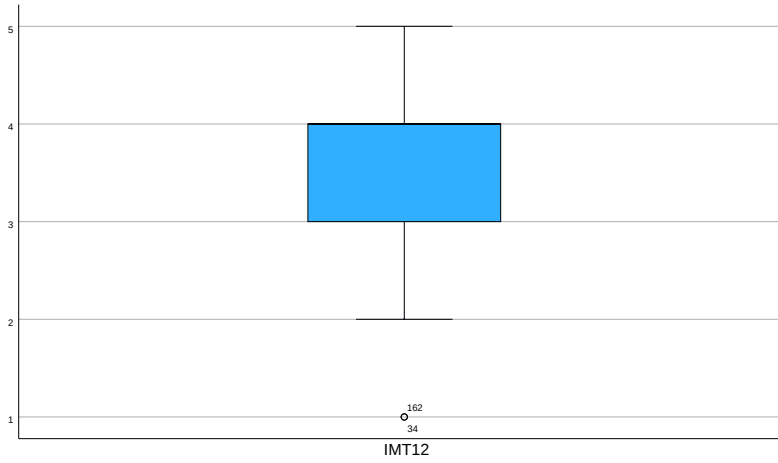
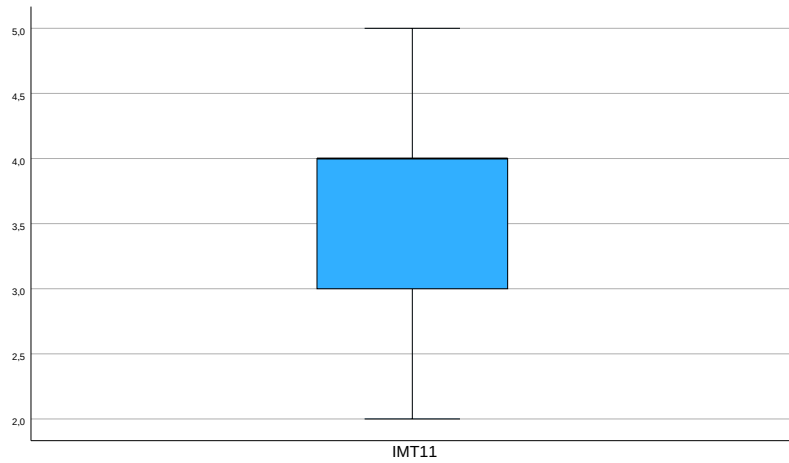
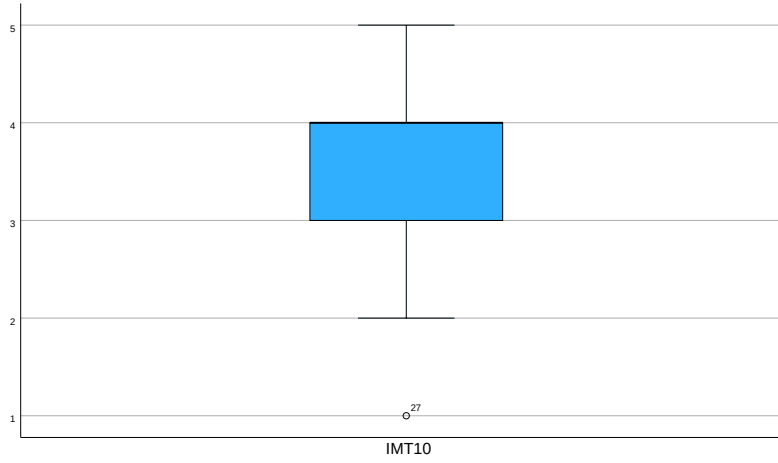
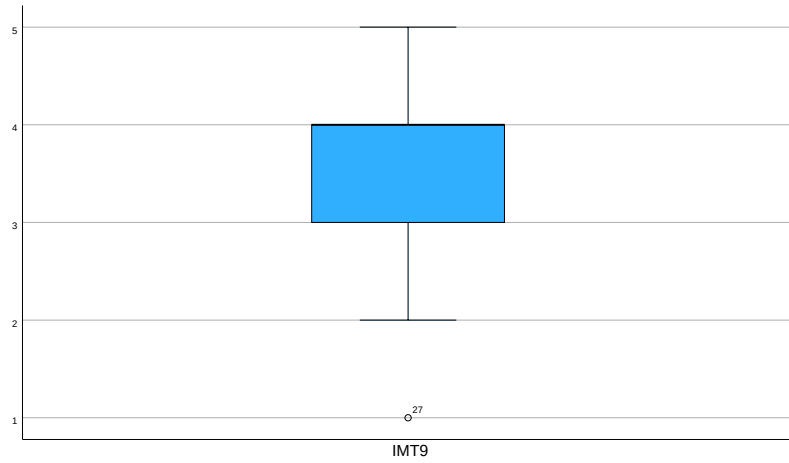


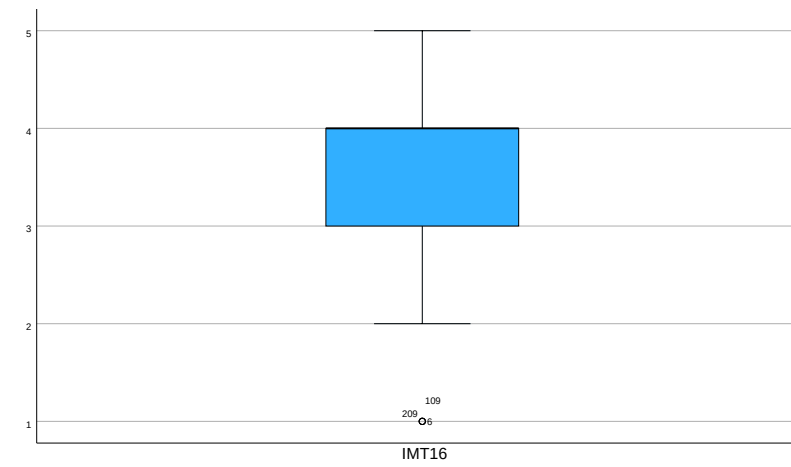
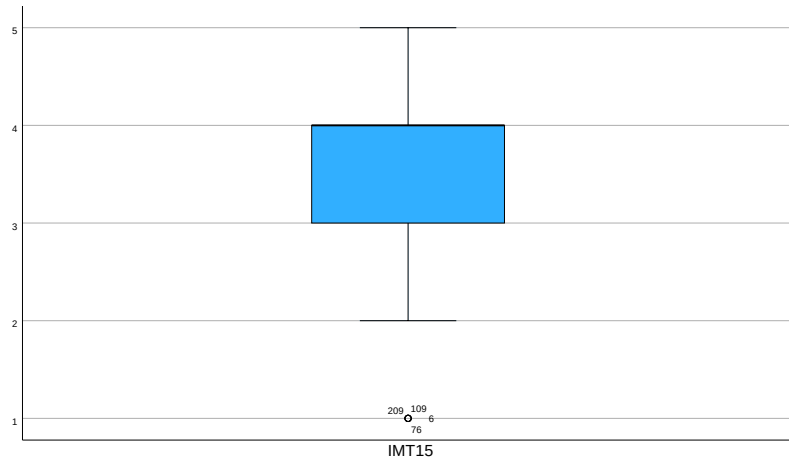
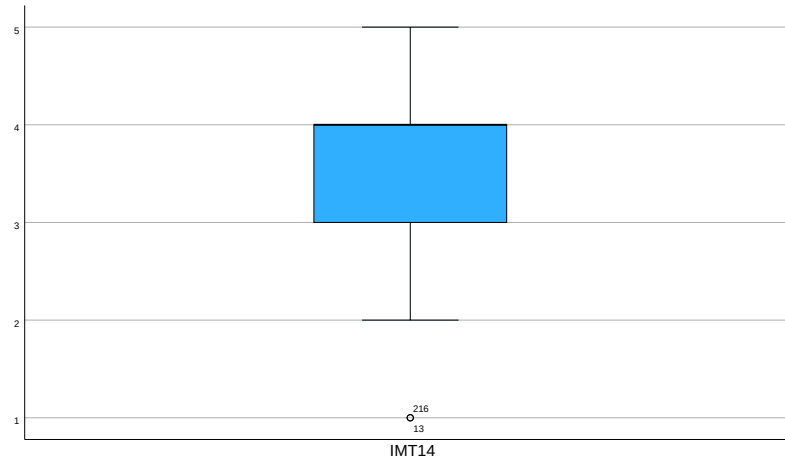
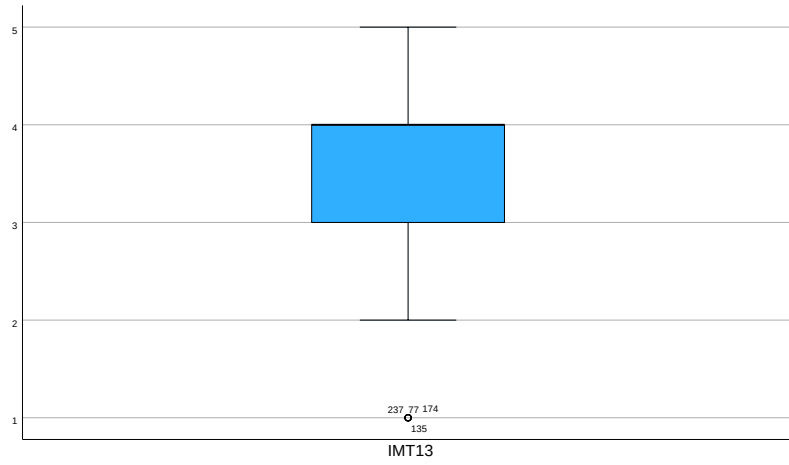


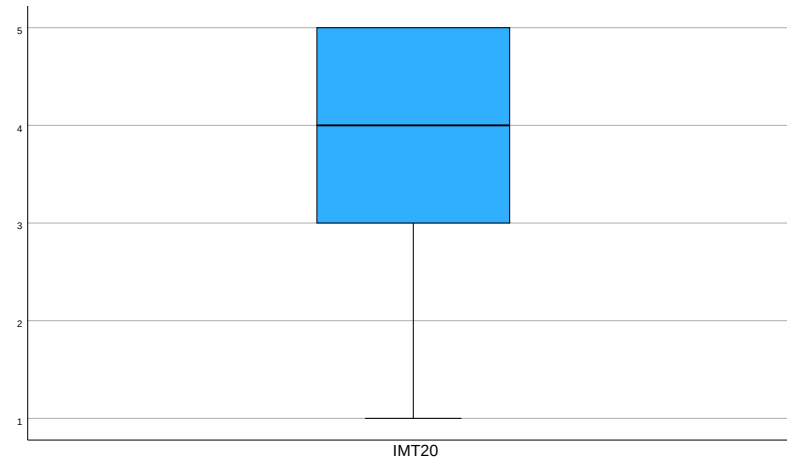
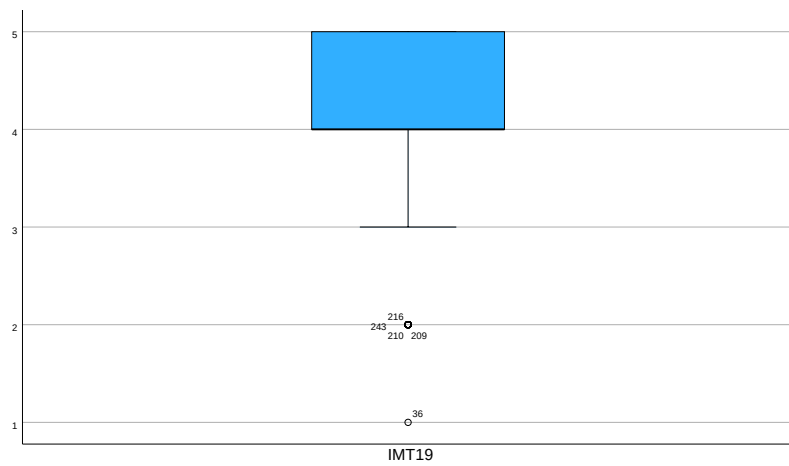
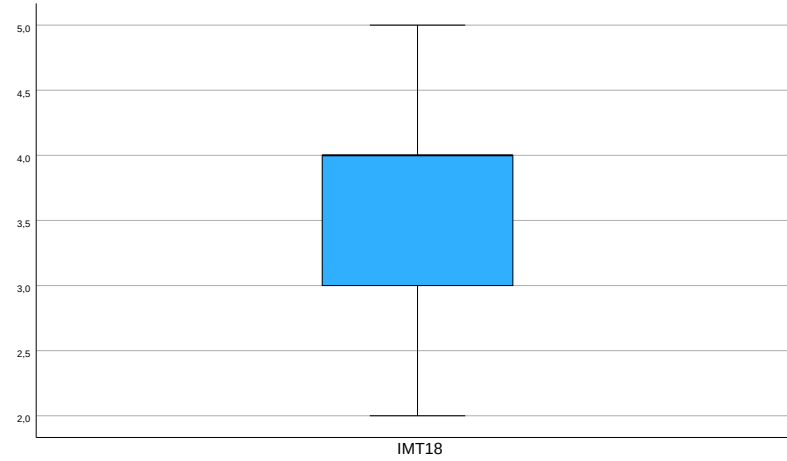
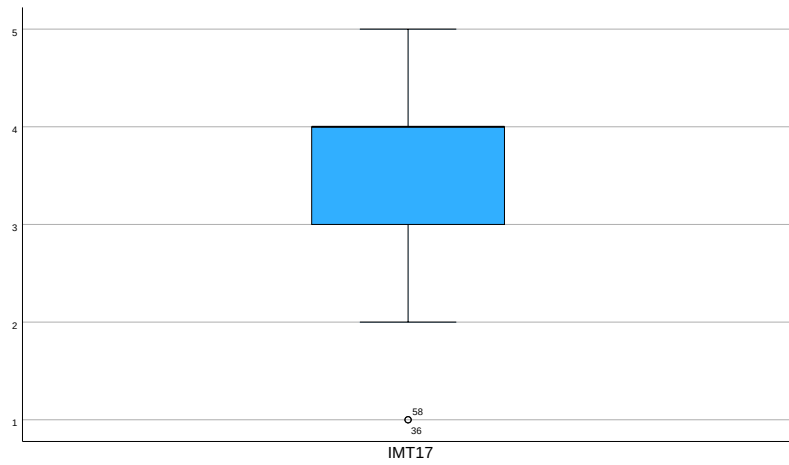


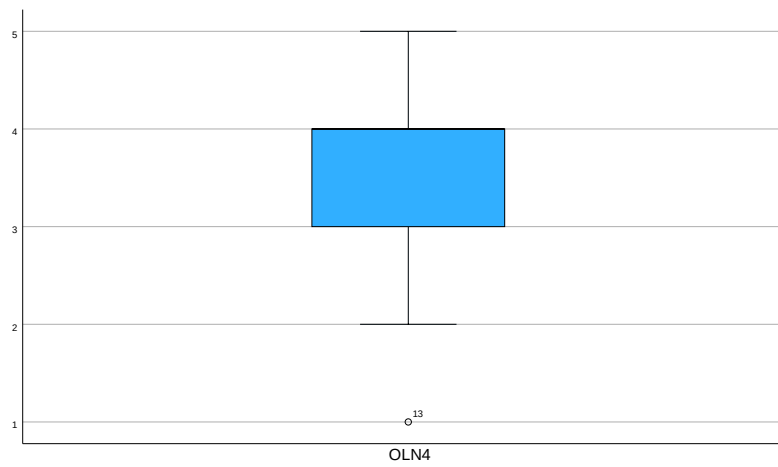
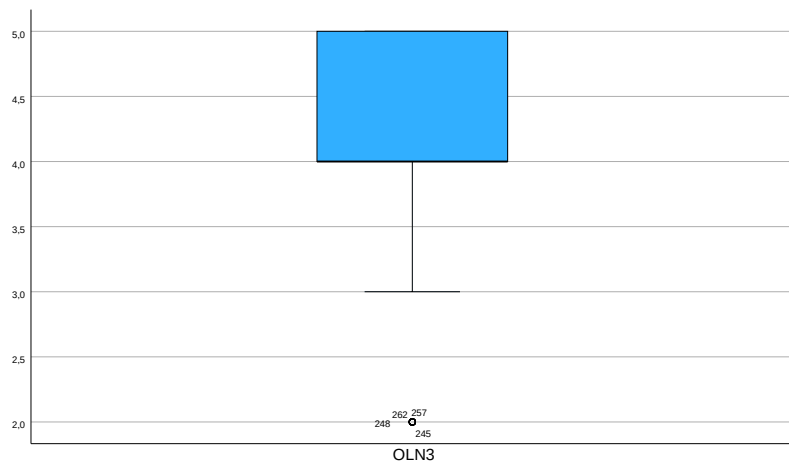
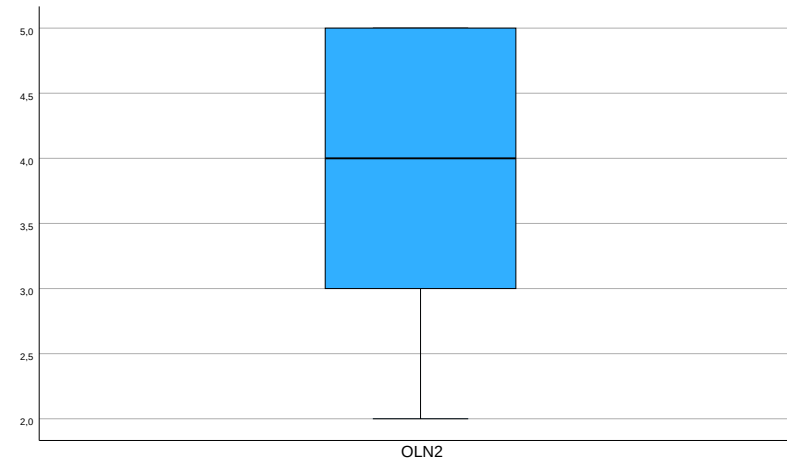
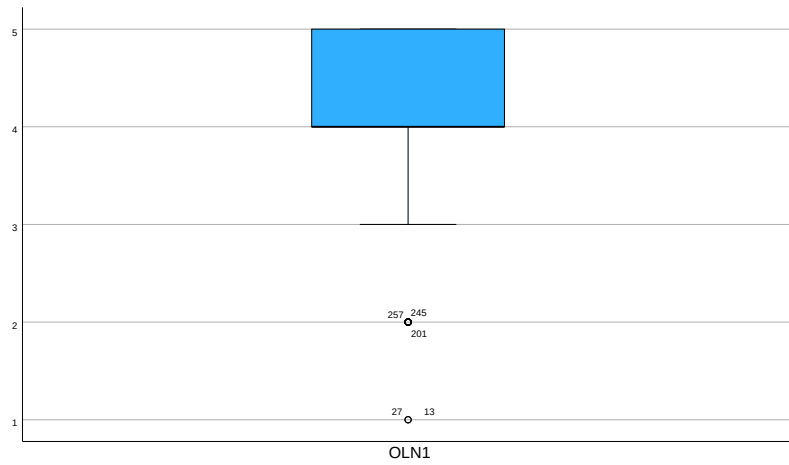


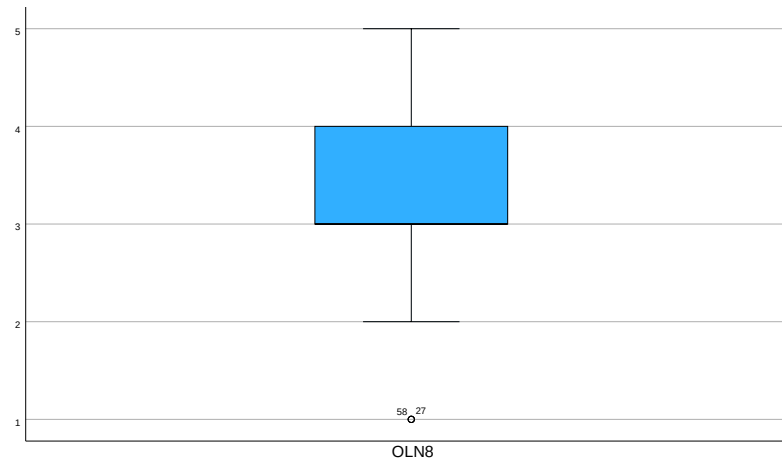
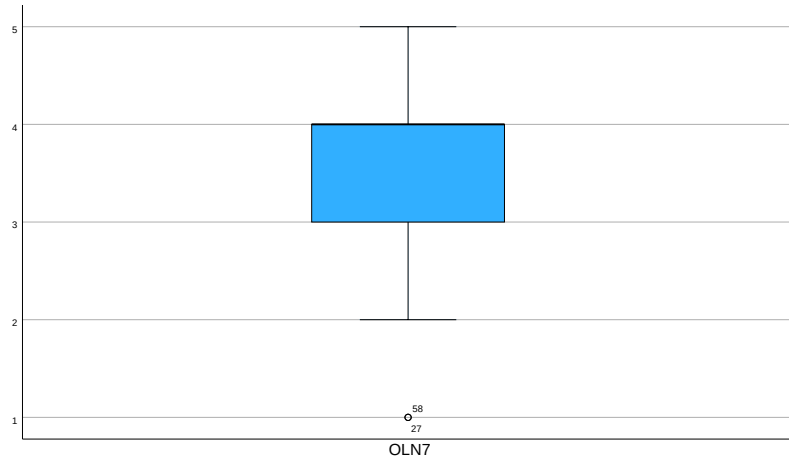
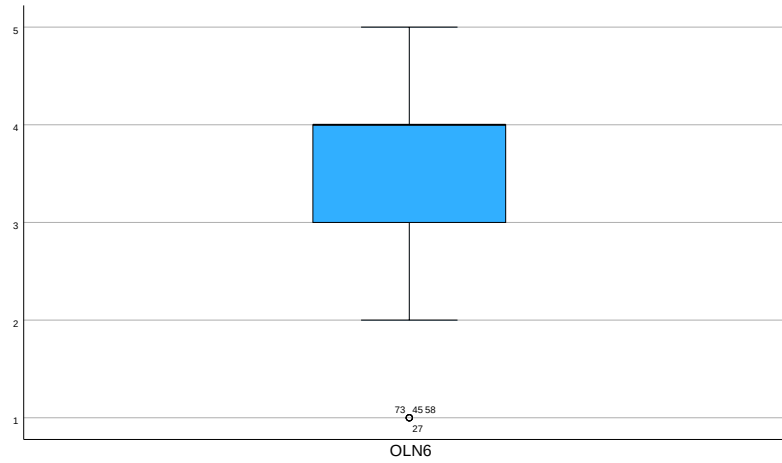
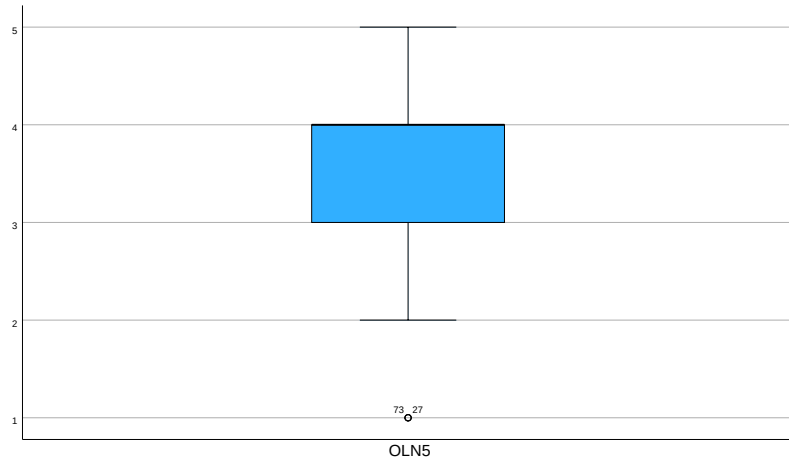


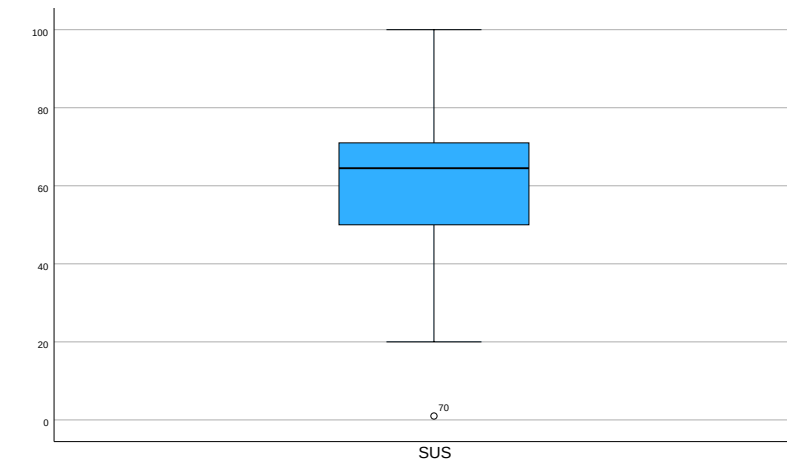
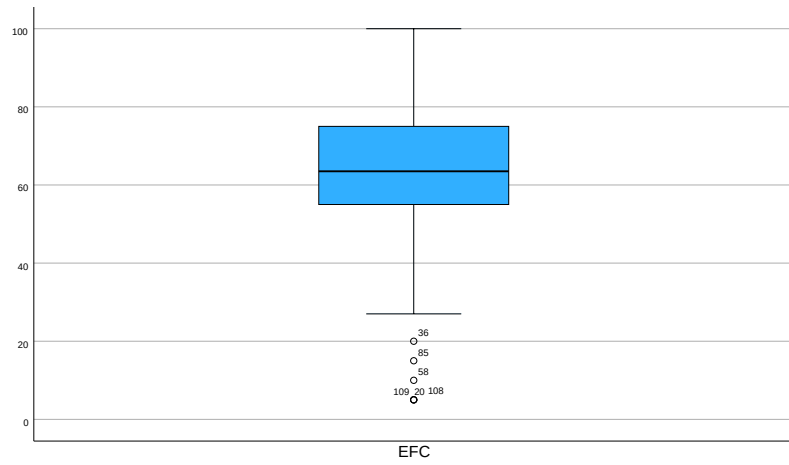
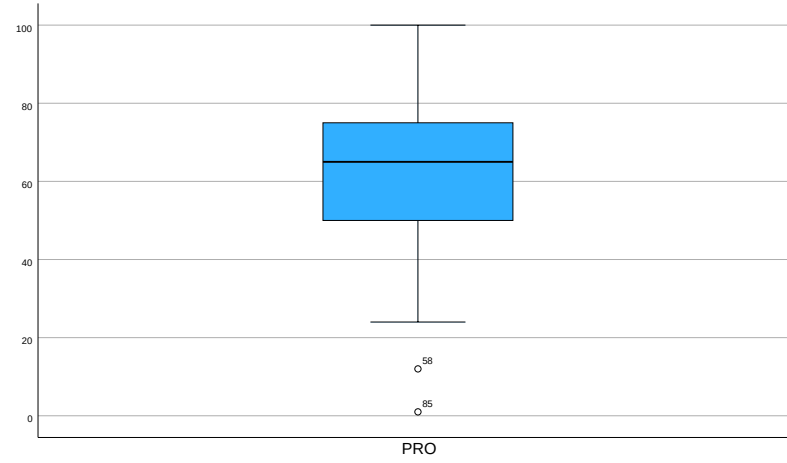
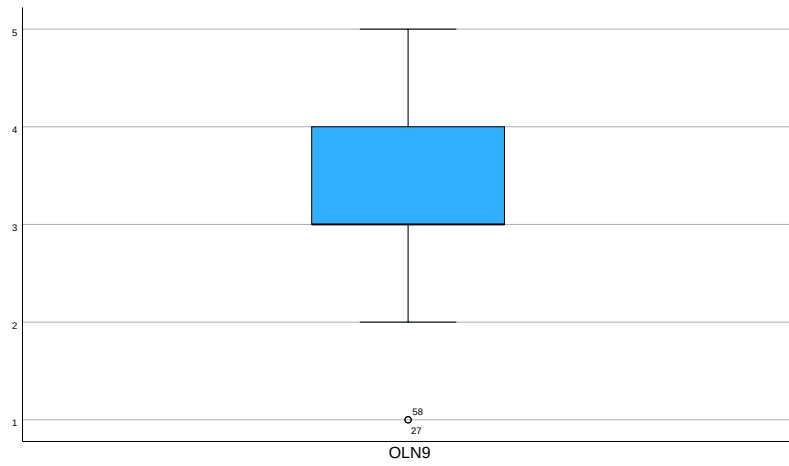












Appendix E Histogram of the indicators from firm survey

