Conceptual Framework for Configurations Development and Measurement: An Approach for Manufacturing Firms During Operational Uncertainty

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Abstract

The fourth industrial revolution (4IR) and fifth industrial revolution (5IR) technologies create the foundation for novel and game-changing methods for managing operations in response to operational uncertainty. The study aims to develop a conceptual framework for a configurations development and measurement approach using operational uncertainty, 4IR/5IR technologies and learning organisation as the influencer of 4IR/5IR technologies' effectiveness The study inductively developed an 11-step analytical conceptual framework grounded on a combination of fuzzy-AHP, PLS-SEM and fuzzy-QCA. The robust framework utilises symmetric and asymmetric approaches to ensure that the outcome moves beyond high value in the dependent variable but in several sufficient and necessary conditions. It provides insights necessary to ensure robust checks to enhance the accuracy of the model by assessing nonlinear effects, endogeneity, unobserved heterogeneity and $PLS_{predict}$ in the partial least squares structural equation modeling (PLS-SEM) and predictive validity in the fuzzy-set qualitative comparative analysis (fsQCA) findings. Finally, the framework provides an approach to measure the long-term impact of the interventions within the firm using difference-in-difference (DiD) and benchmarking the firm's technical efficiencies against industry peers with similar decision-making units (DMUs) using data envelopment analysis (DEA). This framework provides a novel contribution to effective management of operational uncertainty in the manufacturing industry.

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1. Introduction

1.1 Background

Operational uncertainty is a real occurrence that holds significant relevance within the realm of global concerns (Mikaelian, 2010; Sniazhko, 2019; Sniazhko, 2021; Mtotywa & Mohapeloa, 2023). The notion of uncertainty refers to circumstances characterised by a lack of comprehensive or exact information, leading to epistemic constraints or unidentified variables (Sniazhko, 2019). This results in a myriad of challenges in a firm regarding goods availability issues, high prices, labour affordability problems, consistency and reliability problem, maintenance challenges, knowledge retention problems, lower sales, and change in form and quantity of sales, amongst others (Ambulkar et al., 2014; Lu & Shen, 2020; Leung & Sun, 2021). 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 & Linthorst, 2020; 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 (Park et al., 2013; de Waal, 2021). It involves the implementation of world-class practices and achieving superior firm performance relative to competitors (de Waal, 2021; de Waal & Kraaijveld, 2022). 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 are able to adapt to the complexity of their external environment because their organisations make use of environmental variables as sources for effective controls.

1.2 Problem Statement

The problem that this paper addresses is the dearth of conceptual frameworks for configurations development and measurement approaches for manufacturing firms that they can use during times of operational uncertainty. Traditional firms, when faced with operational challenges, would implement best practices such as lean operations and lean purchasing (Azadegan et al., 2013). These are not adequate in a dynamic environment with high levels of uncertainty, when change occurs fast and sometimes with great magnitude, thus making it difficult to effectively forecast and develop the operational response (Patel et al., 2013). As such, global manufacturers have come to recognise that some of these best practices, such as lean production, are inadequate in addressing the intense competitive pressures and other operational uncertainties in the era of the fourth industrial revolution (4IR) (Rosin et al., 2019; Ooi et al., 2023). The emergence of the 4IR and fifth industrial revolution (5IR) facilitated by technological advancements has fundamentally changed the response by a firm and their approach to the traditional lean production processes (Miqueo et al., 2020). The 4IR and 5IR technologies 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 the 4IR/5IR are anticipated to foster flexibility and adaptation, enabling a dual role of reducing uncertainty and coping (Naseem & Yang, 2021; Noble et al., 2022; Santhi & Muthuswamy, 2023). As a result, efforts are ongoing and need to be enhanced to guarantee that businesses can capitalise on the benefits of this transformation from 4IR/5IR technologies while managing inherent operational difficulties. This may be achieved by building configurations for sustainable firm performance centred around leveraging the capabilities of 4IR and 5IR technologies.

1.3 Research objectives

The study aims to develop a conceptual framework as a basis for a configurations development and measurement approach using operational uncertainty, 4IR/5IR technologies and learning organisation as the influencer of 4IR/5IR technologies' effectiveness. This was investigated using the following research objectives (RO):

> RO1: To determine the basis for configurations (gestalts) development that can be built with fourth/fifth industrial revolution technologies for the sustainable performance of a firm during operational uncertainty.
>
> RO2: To determine the measurement approach for accurately predicting the configurations necessary for a sustained firm's performance during operational uncertainty.

The remainder of this paper will evaluate the literature focusing on the complexity and configuration theories that ground this study, followed by reviewing the perspective of operational uncertainty and the capabilities of the 4IR/5IR, before incorporating the perspective of the learning organisation for improved effectiveness of the 4IR/5IR technologies. This is followed by the methodology of the conceptual framework development. The study then discuss the 11-step analytical approach conceptual framework in detail. Finally, we suggest the implications for theory and practice and provide limitations and future directions.

2. Literature Review

2.1 Complexity and configuration theories

The study is grounded on the complexity (Byrne & Callaghan, 2013; Sammut-Bonnici, 2015; Zeynab & Mehrzad, 2017) and configuration theories (Fiss et al., 2013, Pla-Barber et al., 2020). Complexity provides an overarching high-level view which can then be detailed with configuration theory. The complexity theory facilitates comprehension that there are complex adaptive systems that are inherent in firms, particularly during turbulence. It assumes that instability and unpredictability are the norm; successful endeavors in difficult times must accept and use change to their advantage (Byrne & Callaghan, 2013; Larsen-Freeman, 2013). The complexity theory is developed as the theoretical foundation for a firm's operations ecosystem (Zeynab & Mehrzad, 2017). Within the development and application of the theory, there is an evidentiary link for effective application to operations and performance management (Pavlov & Micheli, 2023). This includes operations management areas such as supply chain management (Zhao et al., 2019; Abbasi & Varga, 2022), lean management (Ferreira & Saurin, 2019) and decision support (Baldwin et al., 2010; Reyes, 2013).

Namaki (2018) argued that the complexity theory conveys to a firm's management that the era of hierarchical (predefined) objectives, predetermined logic, and precise control is over. In settings of chaos and disorder, systems are continuously shifting between distinct attractions (dynamic equilibrium), and a tiny adjustment might result in profound and fundamental alterations to the system. Traditional methods are no longer applicable for management regarding change in a complex and chaotic system, and a firm's managers must continuously study the evolution of these systems. Mikaelian (2010) argued that complex systems are susceptible to numerous challenges affecting their capabilities and performance. This underscores the importance of understanding and managing uncertainty within firms for their success and sustainability. The main issue related to the uncertainty principle is that by the time a dynamic problem has been identified and evaluated, the environment has evolved, and the results are partly or no longer relevant.

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) A firm transitions from a complicated style of resolving day-to-day issues to a more complex mode of operation that changes and adapts with its internal and external environment. Smith and Humphries (2004) also highlighted complex theory as a management tool.

The configurational theory has a long history in the fields of strategy and organisation studies (Miller & Friesen, 1984; Meyer et al., 1993). Dess et al. (1993) argued that configuration is a set of interrelated elements or objects that span more than one domain. The configuration approach draws more detailed models due to its ability to analyse more than two domains simultaneously, such as structures, strategy and environment (Matyusz, 2014). This is because the relationships between variables exhibit inherent complexity, occasionally displaying nonlinearity, and abrupt shifts can lead to diverse consequences and outcomes. Variance-based methodologies operate under the assumption that the relationships between variables are linear in nature. However, an alternative approach to address this limitation is to investigate intricate phenomena by considering them as clusters of interconnected conditions (Woodside, 2017).

Venkatraman (1989) identified fit as gestalt (configuration) as one of the perspectives that is a critical building block for theory construction in research areas. Emerging gestalt provides valuable theoretical tools for integrating different variables of interest and encourages investigating and debating their role and impact (Mukherji et al., 2004). These gestalts are referred to as configurations. (Hambrick & Schecter, 1983; Miller, 1986). These are integrated and mutually supportive parts and when multiple variables are employed, it becomes necessary to loosen the degree of precision. A particular perspective that can be employed is the examination of gestalts, which refers to the level of internal consistency observed among a collection of theoretical attributes. The situations that are being described appear to exhibit various gestalts. The arrangement of attributes exhibits a sense of wholeness and organisation, which can offer valuable insights into the concept of equifinality or the sets of internally consistent and equally effective configurations.

The utilisation of a complexity and configuration theory approach presents an opportunity to comprehensively comprehend the patterns generated by these conditions (El Sawy et al., 2010; Zeynab & Mehrzad, 2017). Complexity theory and configuration theories are characterised by the principle of equifinality, which posits that various combinations of antecedent conditions are equally efficacious (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). There are a multitude of factors that can impact the user experience of an information system. In general, various combinations of these factors can account for adopting or utilising such systems and the varying degrees to which these factors are present. This implies that the presence of all factors or antecedents is not necessary for the explanation of adoption or usage. It is probable that a combination of certain factors can adequately account for high levels of adoption or usage. However, there are instances where a particular factor is deemed essential for facilitating widespread adoption or utilisation. Equifinality refers to the idea that more than one combination might be as successful in generating the same result (Fiss et al., 2013; Misangyi et al., 2017).

2.2 Incorporating the perspective of operational uncertainty

Mtotywa and Mohapeloa (2023) identified ten operational uncertainty factors at an external environmental, industrial, and firm level. Environmental factors are growing geopolitical tension, policy and regulatory uncertainty, cost of living-driven consumer behavioural change, pandemic turbulence, energy stability, and security, leadership in sustainability and global responsibility. At the industry level, these are the entrenchment power of large firms and skills for industry future work, while at the firm level, these are generational work behaviour and ethics and process capability and variations. Mtotywa and Mohapeloa (2023) identified four levels of uncertainty that were developed from Courtney (2003), as to levels of uncertainty, and Walker et al. (2003), as to decision-making levels. These are (1) predictable outcomes which occur when the decision-maker can safely assume that all relevant information is already known; (2) alternative futures are where the decision's outcome is contingent on a set of distinct alternative futures; (3) a range of futures where it is impossible to divide these futures into a discrete and exhaustive set of possibilities due to the complexity of the variables at play with additional alternative futures crucial to the decision, and (4) highly uncertain futures where 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 these down.

2.3 Perspective of capabilities of the 4IR/5IR technologies

The technologies of the 4IR and 5IR spur significant advances using technology such as big data analytics, Internet of Things (IoT), blockchain, artificial intelligence (AI) and other advanced algorithms and advanced human-machine interfaces, to create personalised relationships with customers, optimise production chains, and make businesses more efficient (Schwab, 2016; Liao et al., 2018; Mtotywa et al., 2022a; Noble et al., 2022). The Internet of Things (IoT) has a particular focus on enabling technologies, application difficulties, and protocol concerns and the first stage of the IoT might be conceptualised as the revolution that is currently taking place in Internet, mobile, and machine-to-machine (M2M) technology (Al-Fuqaha, 2015; Gamede & Mtotywa, 2022). It was made possible by recent innovations in radio frequency identification (RFID), smart sensors, communication technologies, and Internet protocol standards. The fundamental idea is to develop a new category of software by having intelligent sensors working together in a way that does not require the participation of any humans. Blockchain technology is also becoming increasingly essential, necessitating research into its design and regulation.

The 4IR technologies revolutionised automated manufacturing, asset management, and other industries by collecting, transferring, analysing, and storing data (Liao et al., 2018; Javaid et al., 2020). Data analysis in some industries facilitates rapid decision-making and may also be used as an analytical tool that is well-suited to tracking and controlling uncertainty by enabling near-real-time decision evaluation (Javaid et al., 2020). The 4IR/5IR technologies optimisation of the process with simulation, systems integration for real-time process monitoring (Gamede & Mtotywa, 2022; Noble et al., 2022), supply chain optimisation (Teniwut & Hasyim, 2020; Unhelkar et al., 2022), operational environment benchmarking and future prediction, training and skill development for virtual skills training and simulation, interconnectedness for improved safety and environmental management, root cause analysis and sustainable solution, and personalised relationship with customers(Mtotywa et al., 2022b) To properly evaluate customer/market demands, the "Voice of Customer" (VOC) and process performance "Voice of Process" (VOP), requires the use of statistical techniques to attribute a value to process capability, process performance, and process sigma (or sigma level) throughout the entire production cycle of a product/service (Datta, 2023). Gamede and Mtotywa (2022) posited that establishing control can be an iterative process and control limits are typically considered as experimental thresholds. This ensures that a process is running at or near acceptable target(s) for some natural (common) causes of variation and that no specific causes or concerns are present as a top priority. The process capability can be determined using a control chart to assess the stability of the process under study, which is a prerequisite hypothesis for the calculation.

The 4IR is founded upon the utilisation of CyberPhysical Systems (CPS) and Systems of Systems (SoS). The scope of this topic encompasses the integration of IoT and the incorporation of intelligence across various domains, resulting in the development of intelligent or smart factories, also referred to as the Factory of the Future (FoF). Virtual and physical environments are also integrated, enabling real-time monitoring and collaborative capabilities. Implementing IoT enables the establishment of a network among all machines within factories (Gamede & Mtotywa, 2022). This network facilitates the exchange of information and promotes collaboration, ultimately leading to a flexible and self-adaptive production system throughout the entire supply chain (Nyagadza et al., 2022). Furthermore, the 4IR technologies facilitated the realisation of mass customisation, diagnostics and enabled optimal decision-making. This advances learning and optimisation by integrating information and technologies.

Changing needs, rerouting, major disruptions, and compliance difficulties are only some of the many sources of ongoing disruption in the supply chain (Teniwut & Hasyim, 2020; Unhelkar et al., 2022). Therefore, supply chains necessitate close scrutiny and constant fine-tuning. To automate processes and make better decisions, data scientists analyse data in real-time, and RFID and big data are useful technologies for supply chain. The RFID technology can produce substantial amounts of real-time data, which can be streamed and which prove to be highly valuable in enhancing supply optimisation. In recent years, there has been a notable increase in the adoption of RFID technology across various industries. This is primarily due to its ability to offer big data in real-time, which facilitates the identification, monitoring, tracking, and security assurance of goods (Zhang & Wang, 2020). Thus, RFID technology is essential for digitalisation of supply chains. By utilising automated sensor data, RFID facilitates the analysis of information for the purpose of automation and optimisation.

Despite these positive developments, there is criticism leveled at the fourth and fifth industrial revolutions (Koh et al., 2019). Moll (2023) argued that in comparison to the prototypical first Industrial Revolution, the 4IR is a myth as 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, with a dearth of studies supporting this view. Marwala (2023) responding to Moll (2023) that the assertion that the 4IR does not qualify as a revolution lacks a solid basis. Arguably, it could have been contended that prior to the COVID-19 pandemic, the current state had not yet been attained. Nevertheless, the profound transformations, discernible shifts across various domains, and even the alterations in personal experiences indicate an ongoing revolution. Anshari et al. (2022) recognised the necessity for broader dissemination of knowledge within the framework of the sustainable supply chain. The significance of system implementation lies in its potential to incur costs that may render it financially unsustainable. Considering the potential long-term economic advantages and social and environmental benefits, it is plausible that the implementation of the system is justified.

2.4 Perspective of learning organisation for improved effectiveness of 4IR/5IR technologies

Inadequate knowledge and application, and the acceleration of the implementation of technologies due to the COVID-19 pandemic, are among the influencing factors (Lal et al., 2021; Patanjali & Bhatta, 2022), and sometimes technology overload (Rasool et al., 2022) all contribute to variations in the effectiveness. The progress in manufacturing has led to technologies for COVID-19-smart social distancing tags, internet of things (IoT) and artificial intelligence (Al) and autonomous robots (Sarfraz et al., 2021). There is a raging 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., 2021; Patanjali & Bhatta, 2022).

A business needs organisational learning to improve the effectiveness of the 4IR/ 5IR technologies in improving performance. The increasing prevalence of 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 the 4IR 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) posited 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. Firms that are better able to develop new knowledge, also referred to as "learning organisations," are able to innovate more successfully and adapt to changing environmental conditions more rapidly and efficiently, obtaining a competitive advantage over firms that are unable to do so. The achievement of sustainability in the context of the 4IR is contingent upon a robust commitment to investing in the advancement of organisational learning. This strategic approach is crucial for effectively managing the inherent strengths and threats associated with the 4IR (Ivaldi et al., 2021). The learning process involves utilising individuals' 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), in light of the inherent uncertainty that organisations must confront, 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., 2021).

3. Research Methodology

The current study reports the inductive development of a conceptual framework for configurations and its measurement. The conceptual framework aims to elucidate the concepts being examined by drawing upon pertinent literature and explicating the presumed connections between these concepts (Rocco & Plakhotnik, 2009; Su-ungkavatin et al., 2023). The development of the conceptual framework is influenced by a thorough examination of existing literature and also encompasses emergent concepts (Luft et al., 2022). The framework is aligned with the theory to maintain coherence.

The study uses fuzzy-set qualitative comparative analysis (fsQCA), which uses Boolean algebra to conduct a case-based analysis to investigate interconnectedness, intricate causation, and causal relationships (Ragin, 2008; Misangyi et al., 2017). The fsQCA can be applied using the deductive approach for theory testing and the inductive approach for theory building. The fuzzy-QCA combines the Fuzzy analytic hierarchy process (AHP) technique for prioritising operational uncertainty factors and partial least squares structural equation modeling (PLS-SEM) for symmetrical analysis and as an input to fs-QCA. Combined PLS-SEM and fsQCA were used elsewhere (Woodside, 2013; Zhang & Zhang, 2019; Rasoolimanesh et al., 2021; Silaban et al., 2023). The scores of the constructs obtained through the PLS-SEM analysis of a network of constructs that follow a theoretical framework provide reliable data for conducting fsQCA in order to determine the necessary combinations of conditions that are sufficient to predict the outcome(s) (Rasoolimanesh et al., 2021). This combined technique assists in developing a conceptual framework for configurations and their measurement.

4. Findings and discussion

Configurations can emerge conceptually or empirically, and both are designed to characterise "what" configurations exist in organisations (Duberley & Burns, 1993; Fiss, 2007; Woodside et al., 2018). Figure 1 presents a conceptual framework of the series of steps of the approach indicating the interplay between 4IR/5IR technologies and manufacturing firms during operational uncertainty.

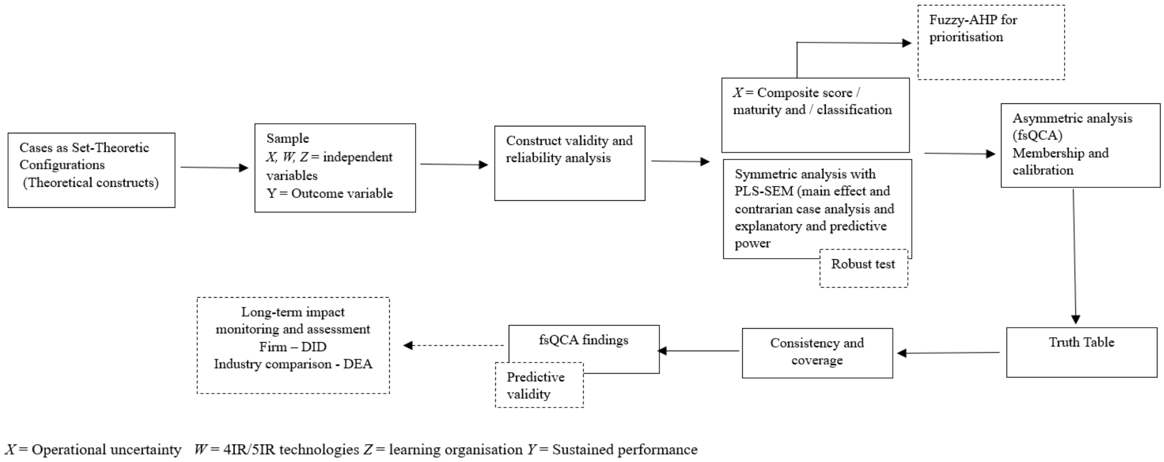

Figure 1: Impact of uncertainty factors on operations for configuration development
Source: Authors' own construct.

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).

4.1 Cases as set-theoretic configurations (theoretical constructs)

Although cases can be interpreted in various ways, such as theoretical entities or empirical units, QCA specifically conceptualiess cases as sets of attribute configurations (Misangyi et al., 2017; Greckhamer et al., 2018). Configurations can emerge conceptually or empirically, and both are designed to characterise "what" configurations exist in organisations (Duberley & Burns, 1993; Fiss, 2007; Cooper & Glaesser, 2010; Woodside 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 (Harlacher & Reihlen, 2014; Damke et al., 2018). The configurations illustrate an arrangement of elements facilitated by intricate interdependent systems established through central organising themes.

The current study posits that *operational uncertainty factors*, *4IR/5IR technologies* and *learning organisation* are key factors critical for sustainable performance during operational uncertainty. These factors are multidimensional and complex, requiring both symmetrical and asymmetrical analysis. The interdependence and interplay between and among these factors gives rise to diverse configurations in varying circumstances. The focus is to assess and delineate alternative trajectories that could potentially result in 'positive performance' and 'negative performance' outcomes. The understanding of the dominant influencing operational uncertainty factor is indicative of their developmental pattern. Implementing a 4IR/5IR technology in response can help to minimise, if not eliminate, the impact of this operational uncertainty on the firm's performance.

The utilisation of configurations also possesses a prognostic capacity, as, within this framework, an organisation can employ diverse perspectives on knowledge as a means 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).

4.2 Sample

Despite being able to develop the initial configurations conceptually, collecting a sample that objectively reflects the realities within the firm is recommended. The fsQCA is designed to work with a small sample size (Ragin, 2008; Fainshmidt et al., 2020). For quantitative analysis, the sample size can range from less than 50 to thousands of cases (Pappas & Woodside, 2021). The sample will be obtained from the survey which investigates each of the variables, which in this study is $X =$ operational uncertainty (Mtotywa & Mahapeloa, 2023), $W =$ 4IR/5IR technologies from the literature (Schuh et al., 2020; Fanoro et al., 2021; Noble, 2022), $Z =$ learning organisation. The instrument is based on single-loop, double-loop and deuteron-learning and is adapted from Wong et al. (2008).

4.3 Construct validity and reliability

Based on the type of sample, the construct validity and reliability are analysed using well-known techniques (Hair et al., 2019). These will include composite reliability (CR), for the construct of interest, convergence validity with average variance extracted (AVE) and discriminant validity with Fornell-Larcker criterion for cross-loading (Chin, 1998), heterotrait-monotrait ratio of correlations (HTMT) (Henseler et al., 2015) and HTMT2 (Roemer et al., 2021).

4.4 Composite score and classification

These levels are obtained from the levels of the operational uncertainty assessment index as based on the following formula (Mtotywa & Mohapeloa, 2023):

$$UAD_j = \frac{\sum_{i=1}^{n} NI_{ij}}{n} \tag{1}$$

where UAD is the uncertainty assessment factor for the final individual factors for a firm or business unit, j. NI_{ij} is the item that constitutes a factor, n is the number of indicators in the factor.

The following formula is used to determine the total composite score for all factors, UIA_j (Mtotywa & Mohapeloa, 2023):

$$UIA_j = \sum_{i=1}^{n} UAD_{ij} \tag{2}$$

A low score indicates low operational uncertainty while a high score indicates high operational uncertainty. A score of ≤ 40 represents predictable outcomes, 41 – 79 indicates alternative futures, 80 - 119 represents a range of future uncertainty (level 3) and ≥ 120 suggests high uncertainty levels (true ambiguity) (Courtney, 2003; Walker et al., 2003).

4.5 Prioritisation

Mtotywa and Mohapeloa (2023) identified ten factors of operational uncertainty within a multidimensional construct at environmental, industry, and firm levels. This provides valuable information that can influence the strategy that the firm adopts together with the implementation of the 4IR/5IR technologies. As such, it will be prudent to use a multicriteria decision-making technique such as the Fuzzy-AHP technique to prioritise the main operational uncertainty factors that are influencing the firm (Kilincci & Onal, 2011; Castelló-Sirvent et al., 2022). The fuzzy analytic hierarchy process (AHP) method utilises the principles of the extent analysis method (Chang, 1996). For the purposes of prioritisation, this author presented a methodology consisting of seven steps for addressing multi-criteria decision-making (MCDM) problems. These steps include: (i) constructing a hierarchical structure to organise the criteria involved; (ii) conducting pairwise comparisons to assess the preferences between each criterion and alternative, and developing a preference scale; (iii) calculating the Fuzzy synthetic extent value; (iv) determining the degree of possibility for each criterion and alternative; (v) identifying the minimum degree of possibility for each criterion and alternative; (vi) normalising the matrix comparison and obtaining a weight vector, and (vii) computing the relative weights and ranking the alternatives based on their performance in relation to the relative weights.

4.6 Symmetric analysis with PLS-SEM - main effect, contrarian case analysis and robust test

Partial least squares structural equation modeling (PLS-SEM) has emerged as a widely accepted and commonly used method for examining intricate connections between observed and latent variables within the realm of social science research including operations management (Peng & Lai, 2012). The $PLS_{predict}$ assesses whether the model has good predictive quality (Shmueli et al., 2019) while PLS-SEM analyses the main effect on the relationship between variables. It is also critical to perform a contrarian case analysis that reveals those instances where *X* is low but *Y* is high or where *X* is high, but *Y* is low, cases that can still arise despite a positive relationship between *X* and *Y* and a substantial effect size of this relationship. Contrarian case analysis supports the necessity for modeling multiple realities by employing complex antecedent configurations (Woodside, 2014). Therefore, it is imperative to employ a modeling approach encompassing multiple realities to comprehend the various combinations of indicators that lead to favorable outcomes (referred to as high *Y*) and the factors that contribute to the absence of such outcomes. In the presence of multiple antecedent conditions, a significant level of *X* may be required for the occurrence of a significant level of *Y*. However, it is important to note that a high *X* level in isolation is rarely adequate to guarantee a high level of *Y*.

Sarstedt et al. (2020) highlighted the importance of robustness in checking the PLS-SEM, focusing on the nonlinear effects for an optimal model, endogeneity assessment and unobserved heterogeneity. In the context of estimating path models, it is customary for researchers to assume a linear relationship. Although linear relationships often provide a reasonable approximation of real-world relationships, it is important to note that this is not always the case (Ahrholdt et al., 2019). Hair et al. (2019) proposed that in cases where the relationship between two constructs is non-linear, the magnitude of the effect size between these constructs is contingent upon both the degree of change in the exogenous construct and its particular value. Researchers can employ a regression equation specification error test (RESET) to evaluate the presence of nonlinearity in relationships. When implementing RESET, it is advisable for researchers to assess the significance of the nonlinear effect specification. If the effect of the interaction term is statistically significant, this indicates that the impact of the exogenous construct becomes stronger (or weaker) as the exogenous variable attains higher values. On the other hand, a lack of statistical significance in the interaction term provides support for the durability of the linear effect.

It is also critical to investigate that there are no issues of endogeneity. The PLS-SEM can assess the presence of endogeneity using Gaussian copula. This can be done across the combination from one copula (independent *X* variable and dependent variable) to multiple copulae (combination of independent variables with the dependent variable *Y*). There are no endogeneity issues if the p-value is greater than 5% but there is endogeneity bias if the p-value is statistically significant, $p < .05$. There are four common sources of endogeneity bias: omitted variable bias (Wilms et al., 2021; Busenbark et al., 2021; Park et al., 2023), simultaneity, measurement error, or common method variance (Jordan & Troth, 2020). These need to be treated to eliminate endogeneity.

With regards to the unobserved heterogeneity, this occurs when distinct subgroups exist within a dataset leading to notable variations in model estimates. In such a scenario, conducting model estimation using the complete dataset will likely yield inaccurate findings. This is likely as there are different levels of operational uncertainty (predictable outcomes, alternative futures, range of future uncertainty, and true ambiguity). This results from the configurations for the optimum necessary and sufficient condition not being the same for different levels of operational uncertainty.

The finite mixture partial least squares FIMIX-PLS method is employed to determine the presence or absence of heterogeneity. The FIMIX-PLS is a valuable tool in this context as it generates model selection criteria that aid in determining the optimal number of segments to retain from the dataset (Hair et al., 2016). The optimum number of segments (OS) is calculated with the following equations:

$$OS = \frac{TO}{NE * 10} \tag{3}$$

where TO is the total number of observations, with NE being the number of variables linked to the endogenous variables. Segments need to have sizes that are more than the recommended minimum size of 5%. The Akaike information criterion (AIC) modified with Factor 3 (AIC3), the CAIC (consistent AIC) and EN (normed entropy statistic) can then be used as the fit indices. Segments need to have a normed entropy statistic which is 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 is done, and the overall minimum segment is selected as the optimum segment. If the optimum segment is 1, then these results confirm that there are no hidden heterogeneity issues and, as such, the data analysed as a whole is acceptable.

Rasoolimanesh et al. (2021) posited that the construct scores derived from PLS-SEM analysis of a nomological network of constructs offers reliable input data for fsQCA to determine the necessary configurations needed to predict the outcome(s).

4.7 Membership and calibration

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 objectives, which is sustainable business performance during operational uncertainty. When these conditions occur constantly, they are termed sufficient conditions within the different cases, 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, 2008; 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 a 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 identify the high and low levels of predictor and outcome to identify the sufficient and necessary conditions.

4.8 Truth table

Rasoolimanesh et al. (2021) highlighted that the "truth table" works on the logic of sufficiency to postulate that when a certain condition is present, the 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, while others can be sufficient but not necessary, while others are necessary but not sufficient and 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 (~), logical AND (*) and logical OR (+) (Rasoolimanesh et al., 2021).

4.9 Consistency and coverage

The consistency and coverage of the configurations assist in identifying the sufficiency and necessity of the configuration for the specific outcome (Ragin, 2008). Consistency highlights the proportion of the cases that are present in a combination for the specific outcome with the consistency calculated (Ragin, 2009):

$$Consistency\ (Con_j) = \frac{\sum(\min Con_j, Y_i)}{\sum(Con_j)} \tag{4}$$

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 sufficiency of the configuration.

Coverage indicates how well the configurations explain the outcome of interest (Woodside, 2013) and is determined using the following formula:

$$Coverage\ (Con_j) = \frac{\sum(\min Con_j, Y_i))}{\sum(Y_j)} \tag{5}$$

A coverage scores 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).

4.10 fsQCA findings and predictive validity of the model

The fsQCA findings provide the outcome of the analysis which is critical for implementation within the firm to understand if the 4IR/5IR technologies improve the firm's performance during operational uncertainty. Papas and Woodside (2021) recommended that the predictive validity of the model be conducted in the study. The assessment of predictive validity pertains to the extent to which a model accurately predicts the outcome of the dependent variable when applied to new and distinct samples. The significance of predictive validity lies in the fact that obtaining a satisfactory level of model fit does not guarantee the provision of accurate predictions by the model.

4.11 Long-term impact monitoring and assessment of 4IR/5IR technologies in manufacturing firms

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 (de Waal, 2017). Analysis of the impact can be analysed using the difference-in-differences (DiD) method and those from the industry with similar structures, the data envelopment analysis (DEA).

Difference-in-differences as the foundation for analysis of intervention impact

The DiD method is frequently used for impact analysis (Fredriksson & Oliveira, 2019; Mtotywa & Mtotywa, 2021; Roth et al., 2023) and is commonly employed to assess the impact of a particular intervention involving the adoption of configurations propelled by technologies associated with the 4IR/5IR. This intervention aims to enhance performance during times of operational uncertainty. Figure 2 illustrates the expected impact of the 4IR/5IR technologies intervention on a firm facing operational uncertainty.

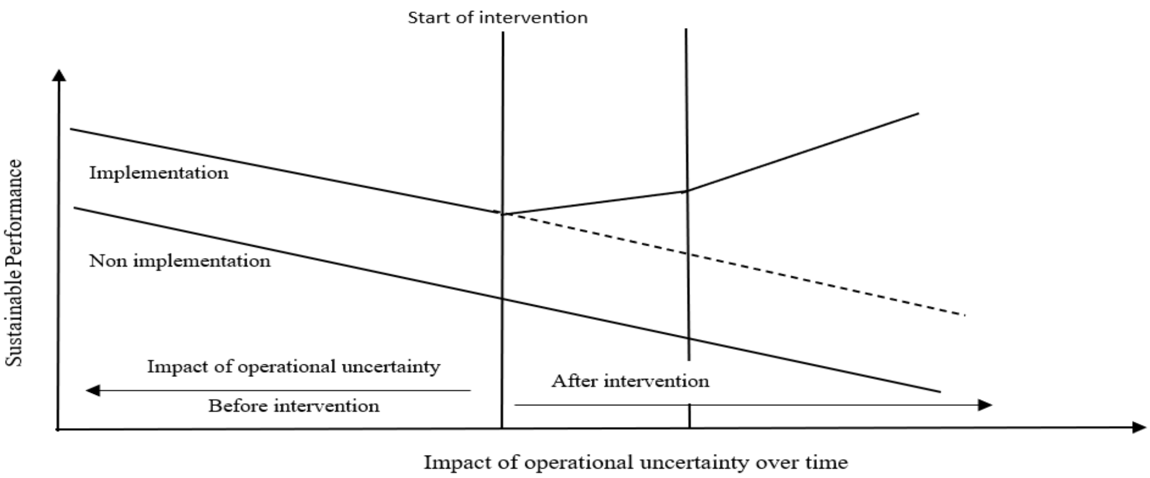

Figure 2: DiD illustration of impact of uncertainty before and after intervention with 4IR/5RI technologies in the firm

Source: Authors' own construction, adapted from Mtotywa and Mtotywa (2022).

The DID method is generally implemented as the interaction term between time and treatment group dummy variables in the regression model:

$$DID_j = \beta_0 + \beta_1 DM_j + \beta_2 IT_j + \beta_3 DM_j * IT_j + \varepsilon_j \quad (6)$$

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 & Migiro, 2016).

Data envelopment analysis (DEA) as the foundation for analysis of comparative performance

Data envelopment analysis (DEA) is used in evaluating and establishing 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 (Malik et al., 2018). 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 peer with similar DMUs.

5. Managerial Implications

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 plays in ensuring the survival and ongoing development of the organisation (Tan & Olaore, 2021). 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. The concept of high performance is closely linked to long-term sustainability (Park et al., 2013) and involves implementing world-class practices and achieving superior performance of a firm relative to its competitors (de Waal, 2021). 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. The main environmental variable is the height of operational uncertainty (Mtotywa & Mohapeloa, 2023) and is associated with the use of fourth and fifth industrial revolution technologies.

The 4IR and 5IR technologies create the foundation for novel and game-changing methods for the management of operations, innovation, and supply chains in response to operational uncertainty. The 4IR technologies offer opportunities for South Africa and the rest of the African continent to re-industrialise (Mtotywa et al., 2022), improving their operations and competitiveness, especially in their manufacturing sector. 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. Our 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). The framework will be useful for firms to identify and prioritise operational uncertainty factors, perform validity and reliability analysis, conduct robustness tests for sustainable performance, as well as monitor and measure long-term impacts. This is a need for the operations managers, who must understand the main sources of operational uncertainty. With ten such sources listed in the study at environmental, industry, and firm levels, such knowledge will inform their strategy and the operational response. Thus, it is recommended that the firm adopt this framework to manage their operations during times of operational uncertainty culminating from multiple sources at the environmental, industry, and firm levels.

6. Conclusions, Limitations, and Future Research

The paper proposes a conceptual framework for configurations of 4IR and 5IR technologies and their measurements for manufacturing firms during operational uncertainty. The study developed an 11-step conceptual framework to predict the outcome (sustainable performance) from the configurations of the fourth and fifth industrial revolution technologies and learning organisation on firms during operational uncertainty. This conceptual framework responds to both the study's objectives, which was to determine the basis for configurations (gestalts) development that can be built with 4IR/5IR technologies for sustainable performance by a firm during operational uncertainty and the measurement approach for configurations for the firm's performance. There are three main theoretical and practical contributions of the study. Firstly, it provides an approach to classify and prioritise operational uncertainty factors so that there is clarity within the firm as to the top factors creating the operational uncertainty that will affect, or are affecting, sustainable performance. Secondly, the developed framework provides a robust approach that utilises 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 accuracy of the model, by assessing the nonlinear effects, endogeneity, unobserved heterogeneity and $PLS_{predict}$ in the PLS-SEM, and the predictive validity in the fsQCA findings. Lastly, it provides an approach to measuring the long-term impact of monitoring and assessment within the firm using DiD and benchmarking the firm technical efficiencies against the industry peer with similar DMUs using DEA. This study is not without limitations, at this stage the conceptual framework is not validated, and future work is required to validate it following the steps proposed in the framework. To further streamline the process, to effectively operationalise and validate all instruments for improved rigor and credibility, the $W =$ 4IR/5IR technologies.

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