

Article

Managing Operational Uncertainty in Manufacturing with Industry 4.0 and 5.0 Technologies

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Abstract

The manufacturing sector drives industrialisation and contributes substantially to economic growth and employment creation. Despite this, it faces the challenges of diminishing size and lack of competitiveness, mainly due to operational uncertainty. The study developed an approach to managing operational uncertainty using Industry 4.0 and 5.0 technologies. It employed a multimethod quantitative design based on the post-positivist paradigm, with data collected from 22 experts and 262 responses from a manufacturing firms' survey. The study employed an integrated fuzzy decision-making trial and evaluation laboratory (DEMATEL) with partial least squares structural equation modelling (PLS-SEM) and fuzzy set qualitative comparative analysis (fsQCA). The fuzzy DEMATEL results reveal that growing geopolitical tension, cost-of-living-driven consumer behavioural change, pandemic turbulence, lack of energy stability and security, and the entrenched power of large firms are causal dimensions of operational uncertainty. Industry 4.0 and 5.0 technologies, with capabilities for scenario planning and supply chain integration, flexible production and mass customisation, real-time system and process monitoring and response, root cause analysis, and sustainable solutions, can manage operational uncertainty. These technologies include artificial intelligence (AI), the Internet of Things (IoT), big data analytics, and, to a lesser extent, advanced robotics, blockchain, and augmented and virtual reality (AR/VR). This study advanced configuration theory and a new integrated methodology (fuzzy-DEMATEL-PLS-SEM-fsQCA) to develop solutions for sustained performance during operational uncertainty in manufacturing. This research offers valuable information to advance the subject, make meaningful changes in day-to-day manufacturing operations, and promote practical real-world problem solving.

Keywords: operational uncertainty; Industry 4.0 and 5.0; organisational learning; sustained performance; fuzzy-DEMATEL-PLS-SEM-fsQCA



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1. Introduction

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 [1,2]. Szirmai [3] 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. Critically, manufacturing also has a reduced susceptibility to economic shocks compared to other industries [4]. The South African Reserve Bank [5] supports this view, arguing that these characteristics have led many countries, including South Africa, to prioritise manufacturing as a sector

for development initiatives. Despite its importance, the manufacturing sector faces challenges [6,7]. Central to these challenges is the diminishing size of this sector in nearly all regions [8] and the lack of competitiveness [9]. In particular, African economies have experienced development and restricted diversification in recent decades, and progress in manufacturing output has stagnated or declined despite efforts to boost the sector [10]. In South Africa, the manufacturing sector was responsible for approximately 13% of the country's GDP in 2021, which is almost half of the 24% in 1990. By 2023, this figure had remained steady at around 13% [11].

The underwhelming performance of manufacturing in Africa in recent years has cast doubt on the prospects of industry-driven development [6,12]. These challenges are exacerbated by the prevailing operational uncertainties that negatively impact manufacturing firms [13,14]. Despite these challenges, Africa can still achieve manufacturing-led industrialisation [15] by improving Africa's global manufacturing competitiveness. This supports the earlier assertions of Signé and Johnson [16], who argued that Africa has the potential to emerge as a major manufacturing hub because of its competitive advantages compared to other developing regions where industrialisation appears to have reached a plateau. These challenges test the resolution of the manufacturing sector in terms of survival, growth, and sustainability [17–19].

A response is required to address such operations management problems. Therefore, manufacturing firms must manage complexity effectively in their operating environment. This is particularly urgent for the manufacturing sector in South Africa and in most African countries. This requires further research, as very little is known about the combined impact and management of operational uncertainty on a firm's performance. This response is essential for enhancing the theoretical development that contributes to the expertise in operations and decision science. This study aims to develop an approach to managing operational uncertainty using Industry 4.0 and 5.0 technologies. The remainder of this paper discusses the theoretical foundation of the study, linking theory with methodology, and the configuration model. This is followed by the methodology, which outlines how the study was conducted and the results of the study. The latter part of the paper discusses the results, the theoretical and methodological contributions of the study, and the implications for manufacturing, while the final section provides the conclusions, limitations, and directions for future research.

2. Theory and Proposition

2.1. Complexity and Configurational Theories

This study is based on complexity [20] and configurational theory [21,22]. Complexity theory provides an overarching high-level view or context that is detailed and operationalised using configurational theory. Complexity theory emphasises dynamic interactions within systems [23] and emergent properties [24,25], whereas configurational theory focuses on the specific arrangements or configurations of elements within a system that lead to particular outcomes [26]. Complexity theory often employs dynamic systems analysis to study emergent behaviours, with operational uncertainty regarded as an emergent behaviour in manufacturing. On the other hand, configurational theory uses set-theoretic methods, such as qualitative comparative analysis (QCA), to identify and analyse configurations to respond to this operational uncertainty [24,27]. In configurational theory, reducing 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 [25]. Configurations serve to evaluate multiple factors, while preserving a significant and coherent aspect of organisational reality and providing a complete framework for a subject [28]. Misangyi et al. [29] posited that the origin of configurational research involves

organisational studies inspired by systems thinking. Configurational theorising is centred on 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—the result in the presence of a particular outcome may differ significantly from the causes that result in the lack of that outcome [26,30].

Linking theory and methodology, we operationalise configurational theory with qualitative comparative analysis (QCA) [27]. Ragin [31] argued that this is an ideal method for evaluating the ‘combined effect’ as well as the ‘interaction relationship’. Qualitative Comparative Analysis (QCA) is one of the most formalised configurational comparative methods [32], as it integrates both qualitative and quantitative methods. QCA is a valuable method for both theory building and testing [33]. Configuration analytical models are useful in theory building, theory extension, and theory testing [29]. Thus, QCA is used for the extension of the theory by identifying necessary and sufficient conditions for outcomes, particularly in complex causal relationships. It is being increasingly used in various disciplines to synthesise evidence and develop theories. Pappas and Woodside [34] also employed a configurational approach to analyse the theory.

2.2. Capability and Barriers to Implementing

Industry 4.0 and 5.0 technologies provide an integrated capability set to reduce and cope with operational uncertainty. Scenario planning and future prediction (SPFP) are strengthened through AI, machine learning, IoT, and advanced analytics, enabling data-driven simulations, pattern recognition, and predictive insights for maintenance, customer behaviour, and market trends [35–38]. Supply chain integration and collaboration (SCIC) leverage IoT, RFID, big data, AI, and blockchain to enhance transparency, resilience, traceability, and coordination amid disruptions [39–42]. Flexible production and mass customisation are enabled by IIoT, AI, and cyber-physical integration, improving efficiency and responsiveness [43–45]. Real-time monitoring and response (RPMR) uses big data, AI, and ML for predictive maintenance, quality assurance, energy forecasting, and optimisation [46,47]. Root cause analysis and sustainable solutions benefit from sensorisation, analytics, quantum computing [48–50], and AR/VR-enabled skills development [51]. Additionally, a protective ecosystem that integrates cybersecurity, blockchain, smart packaging, digital twins, and AI safeguards human–system integrity and combats counterfeiting [52,53]. Despite these capabilities, empirical studies integrating Industry 4.0 and 5.0 technologies to manage operational uncertainty and performance remain scarce, which warrants further research.

There is also an undisputed reality that multiple barriers hinder the implementation of Industry 4.0 technologies in firms, especially in developing countries. Some difficulties emerging nations face in implementing Industry 4.0 technologies include inadequate infrastructure, a lack of a trained and skilled labour force, and problems with scalability and funding [54,55]. Other challenges include increased inequality in the labour market, net displacement of the workforce by technology-driven machines, poor digital culture, and ineffective government policies [56]. Regarding investment costs, some technologies, such as advanced robotics, are very expensive and difficult to implement, especially for small- and medium-sized firms [57].

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 [58].

2.3. Configurations Model

QCA allows research to systematically compare cases and identify the necessary and sufficient conditions for outcomes. It facilitates the exploration of complex causal relationships and formulates theoretical propositions. Through its configurational approach, QCA enables the testing of these propositions against empirical data, thus contributing to the refinement of theories and improving the robustness of research findings [59]. QCA can be applied using a deductive approach for theory testing and an inductive approach for theory building [29]. Pappas and Woodside [34] also employed a configurational approach to analyse a theory, while Cooper and Glaesser [60] demonstrated the value of using asymmetric tests to both advance the theory and provide useful empirical models of the occurrence of multiple realities. QCA uses combinations of causal conditions that result in an outcome [34]. Huang et al. (2024) [61] argued that QCA allows causal complexity analysis and multiple interaction effects associated with conjunctural causation equifinality and causal asymmetry, which are difficult to capture using conventional research methods. In this study, a configuration model was developed to explain sustained performance. Figure 1 shows a set-theoretic configuration model that conceptualises the constructs and demonstrates their multiple asymmetric relationships.

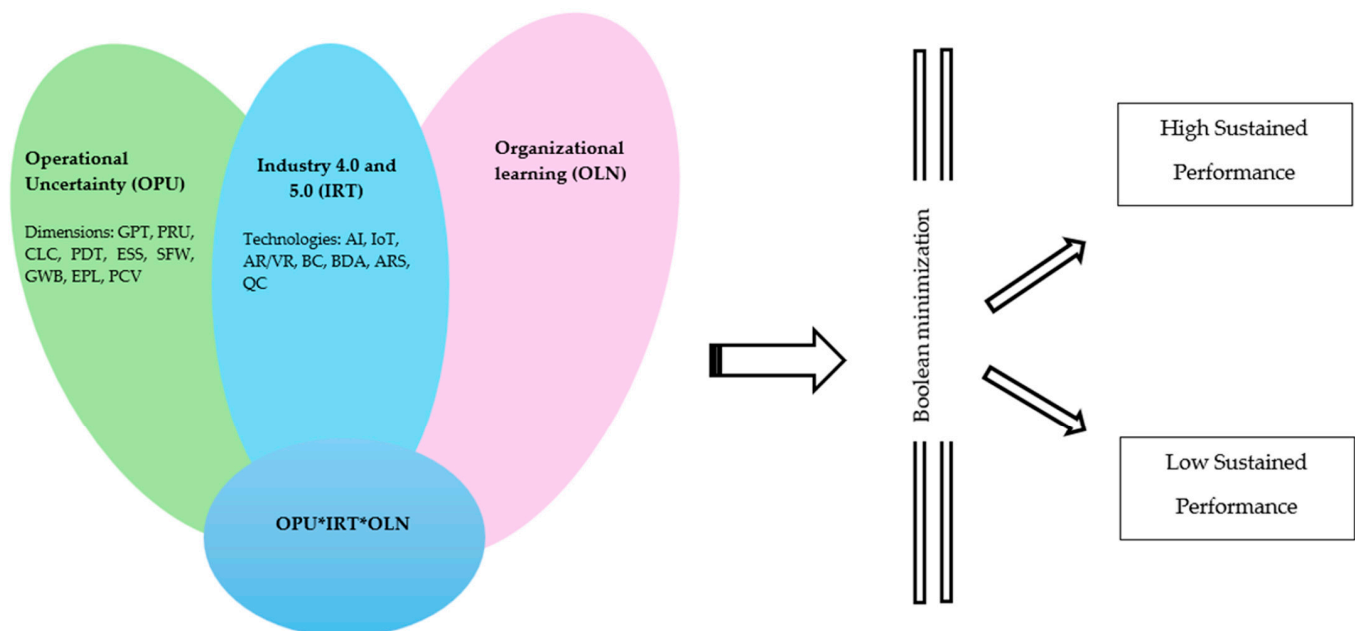


Figure 1. Configurations of the study.

The causal conditions were operational uncertainty (X) and its dimensions [62]. These include geopolitical tension (GPT), policy and regulatory uncertainty (PRU), the cost-of-living-driven consumer behaviour change (CLC), pandemic turbulence (PDT), and energy stability and security (ESS). Additionally, it includes 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) [62].

Proposition 1. *Within these nine dimensions of operational uncertainty, there are some that are causes and others that are effects.*

Second, we have Industry 4.0 and 5.0 technologies (W). These include the Internet of Things (IoT) and enhanced connectivity, artificial intelligence (AI), big data analytics (BDA), augmented and virtual reality (AR/VR), blockchain (BC), advanced robotics and robotic systems (ARS), additive manufacturing (3D printing), and quantum computing (QC) and

their capabilities [63–66]. The capabilities of these Industry 4.0 and 5.0 technologies include (1) scenario planning and supply chain integration (SPSI), (2) flexible production and mass customisation (FPMC), (3) real-time system and process monitoring and response (RPMR), (4) root cause analysis and sustainable solutions (RCAS), and (5) a protective ecosystem (human and system) (PEHS), among others. The third is organisational learning (OLN) [67–69]. Organisational learning has an all-encompassing effect on operations and employee productivity to increase efficiency across the board, in all departments, and at all levels of management [68]. With the help of organisational learning, firms may pool their employees' expertise to solve complex problems [69]. This underpins the importance of learning within firms to improve and achieve their objectives. Firms that are more adept at learning are better positioned to capitalise on emerging opportunities and respond to emerging challenges, particularly those that require considerable organisational change. This strategic approach is crucial to effectively managing the inherent strengths and threats associated with Industry 4.0. Sustained performance may manifest itself through various combinations of constructs, including operational uncertainty, Industry 4.0, Industry 5.0, and organisational learning. The outcomes of interest were analysed using Boolean minimisation.

Proposition 2. *Combinations of OPU dimensions, IRT, and OLN conditions lead to high or low sustained performance.*

3. Methodology

Ethical approval was obtained from the Rhodes University Human Research Ethics Committee (RU-HREC) (approval number 2023-7527-8189). All participants were informed of the study objectives and their rights and informed consent were obtained. This study was part of a larger doctoral study.

3.1. Research Design

This study employed a multi-quantitative method design from a singular paradigm [70,71]. Multimethod is beneficial in research, as it has the ability to generate and test theory in a single study [72]. Adopting multiple methods significantly advanced the field of operational management. In this study, we used a multi-quantitative design, with one phase using expert assessment and the other using a manufacturing-firm survey.

3.2. Sample and Data Collection

The target population for this study consisted of manufacturing companies in South Africa. For experts, non-probability sampling using judgment sampling techniques was used to sample these participants, while, for the firm survey, it was multistage non-probability sampling, which is deemed effective in improving the generalisability of the study. The expert assessment and the survey were conducted in a hybrid form, online and face-to-face, with the online assessment using SurveyMonkey® or email response. Each expert had the opportunity to meet the researcher to explain the study to them.

The study had 22 experts, who were deemed adequate to provide a more comprehensive view while reducing bias and increasing the robustness of the decision-making process [73]. Ferrazzi et al. [74] (p. 4) advanced that 'one of the many strengths of the DEMATEL approach is that it does not require large amounts of data to obtain a robust and reliable result.' These authors used 14 experts in this study and found it adequate. This supports an earlier study by Chen et al. [75], which used 15 experts in the DEMATEL study. Asadi et al. [76] employed 22 experts in their study, further confirming the adequacy of the present study's sample size. This also aligns with the recommended sample size of 20 or more by Chen et al. [77]. The experts for this investigation were selected based on their

competence and experience, which was at least ten years of experience in academia and industry in operations management and policy development [78]. The experts' experience ranged from 11–15 years to more than 25 years. Many experts, especially those in the engineering and production fields, have technical degrees (e.g., BEng, MEng, Ph.D. in Science, and Chemical Engineering), blended with postgraduate management degrees (MBAs, Ph.D., and DBA). Experts were from various manufacturing industries including automotive, food and beverage, metals, machinery and equipment, chemical products, wood products, petroleum, textiles, and clothing. Additionally, there were experts in consulting, academia, and policymaking. For the firm survey, 262 responses were obtained, which equates to a response rate of 68.3% from a determined sample of 384 [79], which is an acceptable response rate [80]. Gauteng had the highest representation (37.0%), followed by Western Cape (14.9%) and KwaZulu-Natal (14.5%). These provinces constituted two-thirds of the respondents (66.4%). This was followed by representations of the Northwest (13.7%), Eastern Cape (6.87%) and Free State (4.58%). The response was from all manufacturing industries, with food and beverage being the largest industry segment, accounting for 23.7%; coke, petroleum, chemical products, rubber and plastic (22.1%); and metal, metal products, machinery, and equipment (20.6%). Transport equipment also had a notable representation (17.6%), while other industries combined totalled 16.0%.

3.3. Data Analysis

The survey data was imported into the IBM Statistical Package for Social Science (SPSS) version 29, where descriptive and inferential statistics were used to analyse the data. Additionally, SmartPLS version 4 was used for measurement and structural model, and fuzzy set qualitative comparative analysis (fsQCA) version 4.1 for fsQCA analysis. Initially, data was coded, screened, and cleaned. The missing values were less than the 10% threshold [81] and there were no issues with common method variance in the data, with Harman's single factor test at 11.67%, which is better than the 50% threshold [82]. Optimal solutions were developed using fsQCA [83,84] from the combination of an enhanced 4-step process.

Step 1: Selection and validation of the causal conditions of operational uncertainty using the fuzzy decision-making trial and evaluation laboratory (DEMATEL);

Step 2: Build configuration;

Step 3: Causal Conditions-Based PLS-SEM Measurement and Structural Models;

Step 4: Develop configurations—solutions (fsQCA).

3.3.1. Step 1: Fuzzy-DEMATEL

In this study, causal conditions were empirically developed using a fuzzy DEMATEL. Fuzzy DEMATEL is a multi-criteria method for visualising the structure of complex cause–effect relationships [85]. This research adapted its approach from Lin and Wu [86] and Yeh and Huang [87] with measures of consistency for the DEMATEL method from Shieh and Wu [88] creating seven sub-steps.

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

Experts denote preferences and assign causalities using triangular fuzzy numbers [89] with the outcome averaged using the following equation:

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

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

Sub-Step 2: Design the fuzzy linguistic scale.

A five-point scale was selected for the operational uncertainty assessment based on the level of its influence on manufacturing operations. The degree of influence was expressed using five linguistic terms and triangular fuzzy numbers (Figure 2).

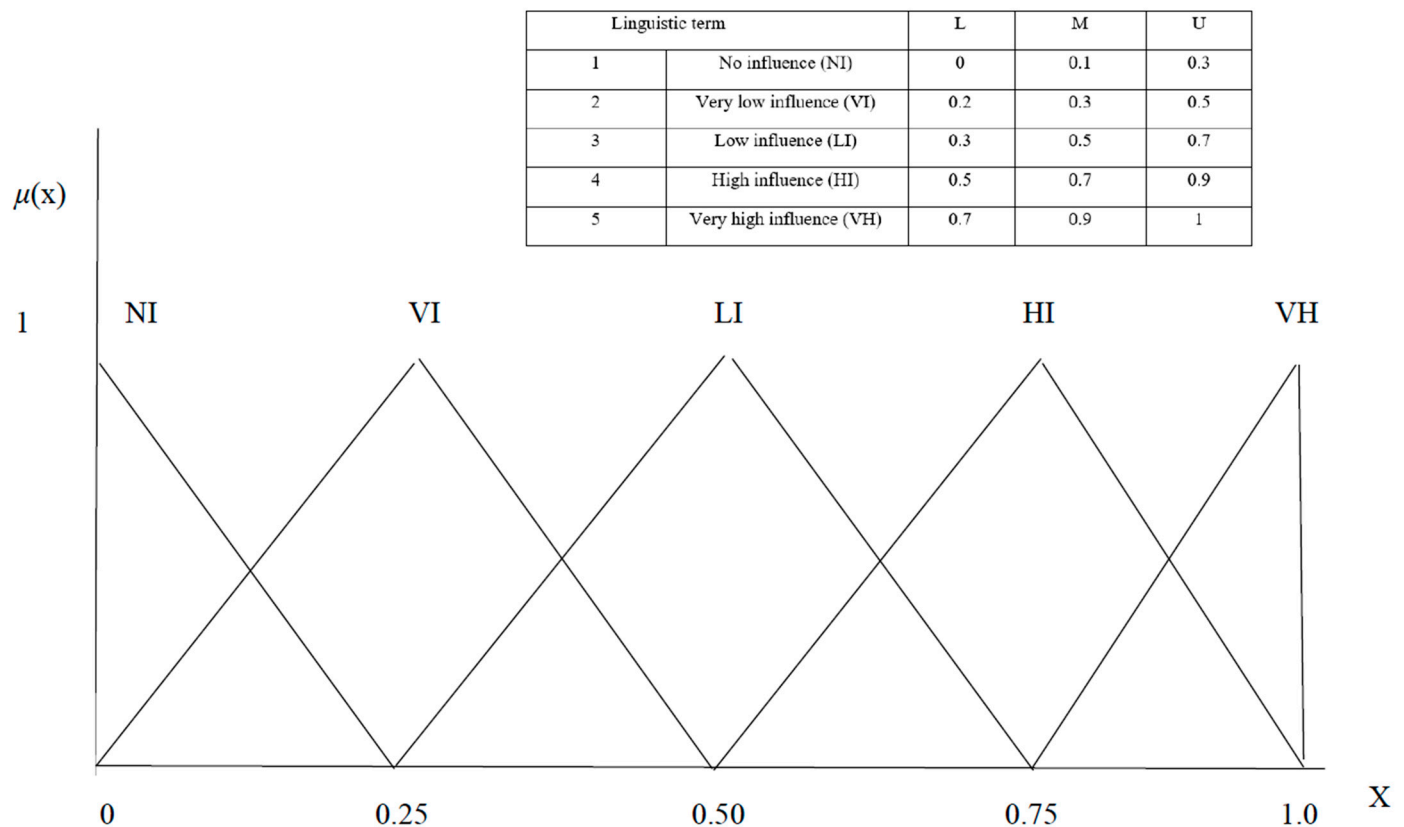


Figure 2. Linguistic terms and triangular fuzzy numbers.

Sub-Step 3a: Generate a fuzzy matrix.

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

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

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

Kendall's coefficient of concordance (W) was used to assess the degree of agreement between decision makers [90]. This method is a non-parametric approach for three or more distinct ranks. Kendall's W was calculated based on the following equation:

$$R_i = \sum_{j=1}^m r_{ij} \quad (3)$$

where i = individual rated criteria (dimension), and m is the number of decision makers where $m > 2$, and $m = 22$ rating n —dimensions, with

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

$$S = \sum_{i=1}^n (R_i - R)^2 \quad (4)$$

where S is the sum of squares statistical deviation over the row cumulates of rank R_i . R is the mean of the R_i values. Kendall's W concordance statistics [91], which range from 0 to 1, can be obtained from the following equation:

$$W = \frac{12S}{m^2(n^3 - n)} \quad (5)$$

In addition, an intraclass correlation coefficient (ICC) analysis was performed with values indicating the level of agreement or reliability among experts' ratings for each construct [92]. The analysis was based on a mixed two-way model using absolute agreement with a test value of 0 at 95% confidence interval. Based on the ICC interpretation, >0.90 equals excellent agreement, 0.75 – 0.90 good agreement, 0.50 – 0.75 moderate agreement, and <0.50 poor agreement.

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

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

Sub-Step 4: Normalise the fuzzy direct relation matrix.

Conversion from a linear scale to a normalised scale was conducted to obtain a compatible scale. Then, the normalised fuzzy direct-relation matrix can be determined using the following equation:

$$\tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{r} = \left(\frac{l_{ij}}{r}, \frac{m_{ij}}{r}, \frac{u_{ij}}{r} \right) \quad (6)$$

where

$$r = \max_{i,j} \left\{ \max_i \sum_{j=1}^n U_{ij}, \max_j \sum_{i=1}^n U_{ij} \right\} \quad i, j \in \{1, 2, 3, \dots, n\} \quad (7)$$

Sub-Step 5: Determine the fuzzy total-relation matrix.

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

$$\tilde{T} = \lim_{k \rightarrow +\infty} \left(\tilde{X}^1 \oplus \tilde{X}^2 \oplus \dots \oplus \tilde{X}^k \right) \quad (8)$$

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

$$\tilde{T} = \begin{bmatrix} \tilde{t}_{11} & \tilde{t}_{12} & \dots & \tilde{t}_{1n} \\ \tilde{t}_{21} & \tilde{t}_{22} & \dots & \tilde{t}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{t}_{m1} & \tilde{t}_{m2} & \dots & \tilde{t}_{mn} \end{bmatrix} \quad (9)$$

and the element of the fuzzy total-relation matrix is expressed as $\tilde{t}_{ij} = (l''_{ij}, m''_{ij}, u''_{ij})$, and is calculated using the following equations:

$$\begin{cases} l''_{ij} = x_l \times (I - x_l)^{-1} \\ m''_{ij} = x_m \times (I - x_m)^{-1} \\ u''_{ij} = x_u \times (I - x_u)^{-1} \end{cases} \quad (10)$$

Sub-Step 6: Defuzzify matrices of total relationships.

$$DF_{ij} = \frac{((u_{ij} - l_{ij}) + (m_{ij} - l_{ij}))}{3} + l_{ij} \quad (11)$$

Sub-Step 7: Causal analysis.

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

$$D_i = \sum_{j=1}^n w_{ij} \quad (12)$$

$$R_j = \sum_{i=1}^n w_{ij} \quad (13)$$

$$D + R \quad (14)$$

$$D - R \quad (15)$$

where D_i is the sum of the rows and 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 was developed to represent the cause–effect diagram.

3.3.2. Step 2: Build Configuration

Fiss [93], and, later, supported by Woodside et al. [94], posited that configurations can emerge conceptually or empirically; both are designed to characterise “what” configurations exist in the area of interest. In this study, the configurations were built based on the model shown in Figure 1. The causal conditions were operational uncertainty (X) dimensions 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).

3.3.3. Step 3: PSL-SEM Measurement and Structural Model

This study analysed the measurement model for validity, reliability, and structural models to understand the level of the relationship between conditions and outcomes using structural equation modelling partial least squares (PLS-SEM). To ensure robustness of the findings, empirical data was conducted to help validate the accuracy of the model, as

well as the robustness and sensitivity test, as it was conducted with finite mixture (FIMIX) segmentation [95]. This was necessary with possible contextual factors such as industry subsector and firm size. The optimum number of segments (OS) was calculated with the following equation:

$$OS = \frac{TO}{NE * 10} \quad (16)$$

where TO is the total number of observations, which was 262 in this research, with NE being the number of variables linked to the results, which is 5, so $OS = 3.28$, equating to three segments. All segments had sizes that were greater 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. 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 size of the segment, 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 (summarised fit = 1547.58). 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 of 0.30. As such, the data set shows one segment, and this is applied for the rest of the analysis.

The model was also evaluated for explanatory power, R^2 , effect size, f^2 , and predictive relevance, Stone–Geisser Q^2 [96]. 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. f^2 is formulated as follows:

$$f^2 = \frac{R_{il}^2 - R_{el}^2}{1 - R_{il}^2} \quad (17)$$

where R_{il}^2 is the R^2 value of the outcome condition when a specific operational uncertainty dimension is included and 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 is its explanatory power, which assesses the proportion of variance in an outcome condition explained by its causal conditions, analysed using the following equation:

$$R^2 = 1 - \frac{SS_{rd}}{SS_{to}} \quad (18)$$

where SS_{rd} is the sum of the squares of the residuals that are unexplained variance in the causal outcome, and SS_{to} is the total sum of squares of the total variance in the outcome variance given as an observed value around the mean. The predictive relevance, Stone–Geisser Q^2 , of the endogenous variables was calculated using the following equation:

$$Q^2 = 1 - \frac{SSE}{SSO} \quad (19)$$

3.3.4. Step 4: Develop fsQCA—Solutions

The fsQCA was developed based on Boolean algebra, and 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 were used: negation operations ($\sim$), logical AND ($*$), and logical OR ($+$) [97]. The input of the

conditions to the fsQCA was the standardised latent scores from PLS-SEM [97,98]. This was followed by the identification and assignment of observations of the set of members [31], calibrated based on the percentile approach [97]. This percentile uses 3 = full membership, 0 = crossover, and −3 = non-membership, where the full membership represents 99.9% percentile and −3 is the 0.1% percentile [97]. Calibration allowed for the analysis of the data and identified the high and low levels of predictors and outcomes to identify sufficient and necessary conditions. The cutoff frequency for conditions (raw coverage) was greater than or equal to 3 for the analysis. This helps to ensure that very few conditions regarded as not meaningful are filtered out. The consistency and coverage of configurations help identify the sufficiency and necessity of the configuration for a specific outcome [31]. Consistency highlights the proportion of cases that are present in a combination for a specific outcome with the consistency calculated as follows [31]:

$$\text{Consistency} (Con_j) = \frac{\sum(\min Con_j, Y_i)}{\sum(Con_j)} \quad (20)$$

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 , and $\min$ 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 [97,99] and is determined using the following equation:

$$\text{Coverage} (Con_j) = \frac{\sum(\min Con_j, Y_i)}{\sum(Y_j)} \quad (21)$$

A coverage score of 0.2 confirms the sufficiency of the configuration with fuzzy set membership scores higher than 0.5, which was obtained from the configurations [31,97].

4. Results

4.1. Causal Conditions of Operational Uncertainty with Fuzzy DEMATEL

The purpose of this decision was to determine the relationships and interdependence of the factors. This is based on nine dimensions of operational uncertainty that are used as sets of criteria. Kendall's W concordance degree scale with its corresponding chi-square (χ^2) measured the agreement and consistency of decision makers. All dimensions had a Kendall's $W > 0.60$ which indicates strong agreement [100], except for GWB with Kendall's $W = 0.48$ indicating moderate to strong agreement (Table 1). The analysis was also conducted with intraclass correlation (ICC), which indicated the level of agreement or reliability between the experts' ratings for each construct (Table 2).

Table 1. Kendall's W of concordance for dimensions.

Dimensions	Kendall's W	χ^2	Df	p -Value
GPT	0.789	138.9	8	<0.001
PRU	0.722	127.1	8	<0.001
CLC	0.751	132.2	8	<0.001
PDT	0.782	137.6	8	<0.001
ESS	0.688	121.1	8	<0.001
GWB	0.480	84.52	8	<0.001
SFW	0.613	108.0	8	<0.001
EPL	0.629	110.6	8	<0.001
PCV	0.850	149.6	8	<0.001

Table 2. Intraclass correlation.

	Intraclass Correlation	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	p-Value
PCV	0.989	0.975	0.997	87.987	8	168	<0.001
PRU	0.986	0.969	0.996	75.853	8	168	<0.001
CLC	0.993	0.984	0.998	150.999	8	168	<0.001
PDT	0.994	0.987	0.998	164.978	8	168	<0.001
ESS	0.989	0.974	0.997	96.168	8	168	<0.001
GWB	0.953	0.894	0.987	25.371	8	168	<0.001
SFW	0.969	0.931	0.992	36.365	8	168	<0.001
EPL	0.985	0.966	0.996	69.840	8	168	<0.001
GPT	0.979	0.952	0.994	55.950	8	168	<0.001

All constructs had an ICC interpretation of >0.90. The results suggest excellent agreement among the experts. The arithmetic mean was then developed from the experts' assessments to generate a direct relation matrix. The generated direct relationship matrix was the same as that of the pairwise comparison matrix of the experts. The conversion of a linear to a normalised scale was conducted to obtain a compatible scale. Subsequently, the normalised fuzzy direct relation matrix was determined. The fuzzy total relation matrix was determined using this system. The fuzzy total relation matrix is critical for identifying and quantifying causal relationships among factors in this complex system. A causal relation analysis was performed to determine the most important factor and how it was classified to understand the cause and effect (Table 3).

Table 3. Output of the 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 3 shows the model of significant relationships that focuses on 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) are placed on the vertical axis. The coordinate system determines the position and interaction of each factor with a point in the coordinate system (D + R, D – R).

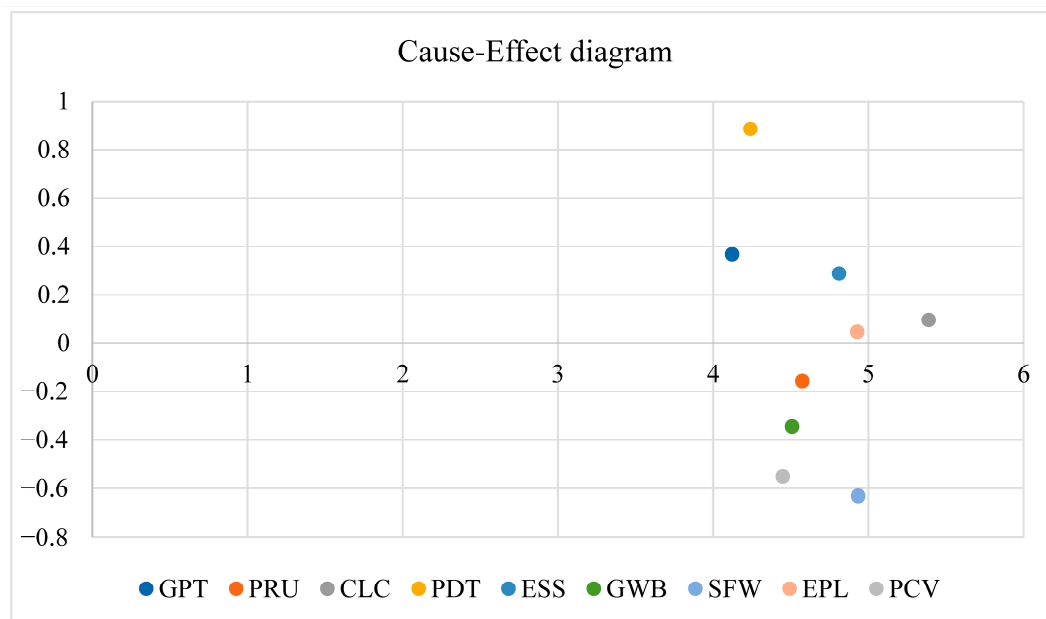


Figure 3. Cause-and-effect diagram.

The horizontal vector ($D + R$) represents the degree of importance of each dimension in the system. In other words, ($D + R$) indicates both the impact of factor i on the entire system and the impact of system factors on the factor. Regarding the degree of importance, CLC is first and SFW, EPL, ESS, PRU, GWB, PCV, PDT, and GPT are next. In this study, GPT, CLC, PDT, ESS, and EPL were considered causal variables, and PRU, GWB, SFW, and PCV were regarded as effects. The results support Proposition 1, which says that, within these nine dimensions of operational uncertainty dimensions, there are some causes, while others are effects.

4.2. Conditions for Building Configurations

Table 4 provides information on the conditions for the building configurations. The building approach was that the model must have more than one causal condition, but not more than seven causal conditions. Models with more than seven causal conditions can be constructed in principle but are not ideal [101].

Table 4. Conditions for fsQCA analysis.

Causal Condition Operational Uncertainty (X)	Causal Condition Industry 4.0 and 5.0 Technologies (W)	Causal Condition Organisational Learning (Z)	Outcome (Y) Sustained Performance
Model I: Growing political tensions (GPT)	Scenario planning and supply chain integration (SPSI) ** Flexible production and mass customisation (FPMC) Real-time system and process monitoring and response (RPMR) IoT, AI, ARB, BCC		
Model II: Cost-of-living-driven consumer behavioural change (CLC)	Scenario planning and supply chain integration (SPSI) Flexible production and mass customisation (FPMC) IoT, AI, BCC, ARB, BDA *	Organisational learning (OLN)	Sustained performance (SPF)
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		

Table 4. Cont.

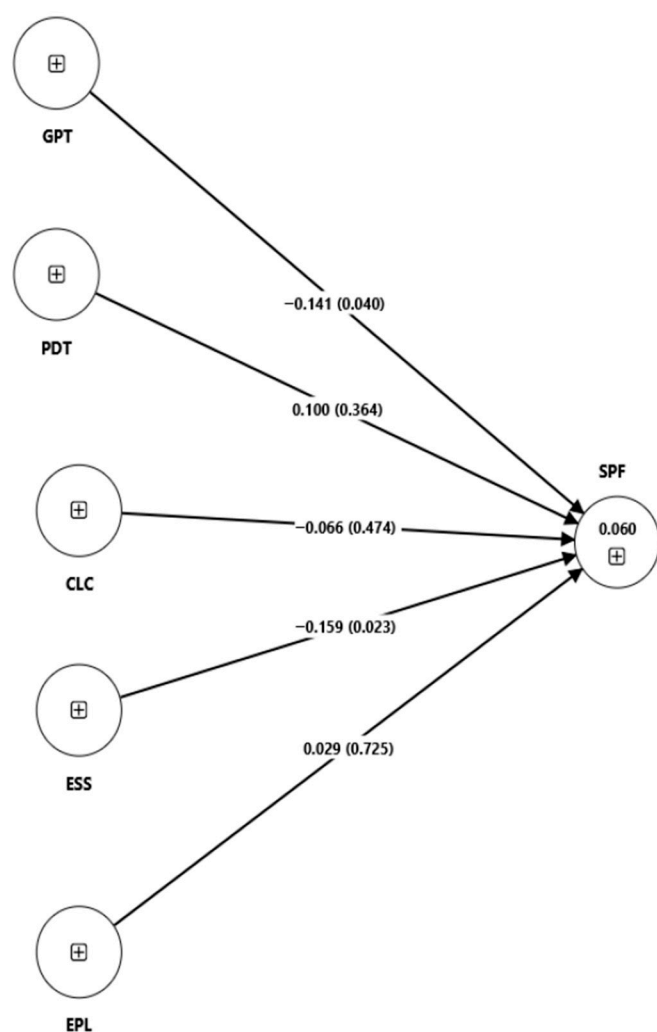
Causal Condition Operational Uncertainty (X)	Causal Condition Industry 4.0 and 5.0 Technologies (W)	Causal Condition Organisational Learning (Z)	Outcome (Y) Sustained Performance
Model IV: Operational uncertainty of energy stability and security (ESS)	Real-time system and process monitoring and response (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		

* BDA—excluded, ** SPSI—developed from integration of SPFP and SCIC due to discriminant lack of validity.

Given the large number of parameters involved, the results can become difficult to interpret and, therefore, such models should be avoided. At the same time, these authors explained that a single causal condition is rarely sufficient to explain the presence of a particular outcome.

4.3. Structural Models—Direct Effect of Causal Model

The measurement and structural model for the five casual conditions are shown in Figure 4. The model was analysed and showed a good fit using SRMR = 0.078.



	α	ρ_A	ρ_C	AVE
CLC	0.758	0.792	0.844	0.577
EPL	0.800	0.812	0.869	0.624
ESS	0.739	0.767	0.849	0.653
GPT	0.711	0.725	0.814	0.524
PDT	0.685	0.757	0.822	0.608
SPF	0.845	0.866	0.905	0.762

	CLC	EPL	ESS	GPT	PDT	SPF
CLC						
EPL	0.542					
ESS	0.469	0.536				
GPT	0.576	0.649	0.600			
PDT	0.492	0.304	0.579	0.452		
SPF	0.156	0.147	0.227	0.218	0.084	

	VIF	R^2	Q^2	f^2 SPF
SPF		0.060	0.005	
CLC	1.374			0.003
EPL	1.514			0.001
ESS	1.491			0.018
GPT	1.489			0.014
PDT	1.275			0.008

SRMR = 0.078

Figure 4. Measurement and structural model of causal conditions with outcome, SPF.

This was a good fit as it was better than both the conservative value of 0.080 [102] and the recommended threshold of 0.10 [103]. The model had good reliability and validity, with all values for reliability > 0.7 , AVE for convergence validity > 0.50 , and discriminant validity using Heterotrait–Monotrait (HTMT) less than $H_{0.85}$. The model had acceptable explanatory and predictive powers. This is important because the validity and utility would be compromised if it did not have such capabilities. The model had acceptable predictive power with a Stone–Geisser $Q^2 > 0$. Although the model had a lower $R^2 = 0.060$, it was deemed acceptable because the model demonstrated an acceptable predictive relevance (Q^2) [104], as well as model performance with an acceptable SRMR. The path coefficients for the structural model show that GPT has a statistically significant negative relationship with a sustained performance (SPF) ($\beta = -0.141, p < 0.05$). There was also a statistically significant negative relationship between ESS and SPF ($\beta = -0.159, p < 0.05$). The other three paths are not statistically significant. As such, the focus of fsQCA was on two significant pathways.

4.4. Measurement Models for fsQCA Solutions

4.4.1. Geopolitical Tension-Based Model (Model I)

The measurement and structural analysis of 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 the reliability, with a Cronbach alpha and composite reliability ≥ 0.60 (Table 5). The measurement model also confirmed the discriminant validity for Model I, with HTMT less than $H_{0.85}$ (Table 6).

Table 5. 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

Table 6. 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	

4.4.2. Energy Stability and Security-Based Model (Model IV)

Table 7 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 ≥ 0.50 , ranging from 0.531 – 0.751 .

Table 7. 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 also had good discriminant validity with HTMT values less than $H_{0.85}$ (Table 8).

Table 8. 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	

4.4.3. 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 were confirmed with $\alpha = 0.763$ – 0.845 , while those for $\rho_A = 0.792$ – 0.905 and $\rho_c = 0.832$ – 0.905 (Table 9). The discriminant validity was confirmed with the HTMT with all values below the threshold of 0.85 ($H_{0.85}$) (Table 10).

Table 9. Reliability and convergence validity for 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

Table 10. Discriminant validity with HTMT for 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	

4.5. fsQCA Solutions

4.5.1. Geopolitical Tensions

fsQCA solutions based on latent-variable scores were obtained for conditions with geopolitical tension. The analysis and solutions were based on the Quine–McCluskey model algorithm. The causal conditions were GPT, OLN, SPSI, FPMC, RPMR, AI, and BCC, while the outcome was SPF. Unique latent variable (LV) scores developed from the truth table were analysed using logical minimisation to identify the sufficient and necessary conditions. Raw consistency measured the consistency of a configuration that leads to an outcome. A total of 32 alternatives were produced from the truth table after removing alternatives with fewer than three cases (cutoff = 3). A standard analysis was conducted that included causal combinations to achieve sustainable performance during growing geopolitical tensions. A threshold of ≥ 0.75 [105] was used as the consistency guide, and a more stringent guide (>0.80) from other authors such as Ragin [31], with coverage greater than 0.2. This was considered sufficient to generate the desired outcome. Intermediate and parsimonious results were combined to identify core and peripheral conditions [106]. When examining parsimonious solutions, SPSI and $\sim$ cGPT were present in both solutions and had a high consistency and coverage, indicating that they were the core conditions, while the others were peripheral conditions. These core causal conditions are strongly linked to outcomes by leveraging present or absent conditions [31]. The analysis produced 12 solutions for a high sustained performance (SPF). In Table 11, the presence of the condition is indicated by a black circle, while the absence is indicated by an empty circle, and the blank space indicated by ‘do not care’ [106]. A large circle denotes the core condition, whereas a small circle represents the peripheral condition. The coverage and consistency were good. The coverage indicates how well the combination of conditions explains the outcome. In these results, it was 0.832, implying that the solution covered approximately 83.2% of the cases. The consistency accounts for how well the combination of conditions consistently predicts the outcome, which, in this case, was 0.799, which implies a consistency of 79.9%. Among these 12 solutions, four had the presence of geopolitical tension (GPT), which is the main focus, as it is assumed to be present in the firm. These are solutions 1, 7, 8, and 10, respectively.

Table 11. Sufficient configurations of high sustained performance in the presence of geopolitical tension and Industry 4.0 and 5.0 technologies capabilities and organisational learning.

Configuration	Solution											
	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 = $f(\text{GPT, OLN, SPSI, FPMC, RPMR, AI, BCC})$

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.

To achieve sustained performance in the presence of GPT, it can be combined with solution 1 (AI in the absence of FPMC, RPMR, and BCC), solution 7 (OLN, FPMC, and AI), solution 8 (SPSI, FPMC, and AI in the absence of BCC), and solution 10 (AI in the absence of OLN, FPMC, and BCC). Six solutions showed the achievement of high sustained performance in the absence of GPT. The necessary condition analysis is conducted for these solutions. The necessary condition is regarded as a superset of the outcome [107]. In this analysis, the SPSI had strong consistency (0.802); a coverage of 0.793 appeared to be a candidate to explain the variations in the high SFP. This was despite not reaching >0.9. Despite this, in the strictest terms, these solutions have no necessary conditions [31]. Four specific sub-propositions were tested based on solutions 1, 7, 8, and 10 in terms of the achievement of high sustained performance in the presence of geopolitical tension when managed with Industry 4.0 and 5.0 technologies. Solutions 1 and 10 were identical in the presence of GPT and AI. The other three sub-propositions are provided in Figure A1a–c. The X-axis typically represents the degree of membership in a causal condition, whereas the Y-axis represents the degree of membership in the outcome [105]. Consistency measures the degree to which cases with high membership in the condition also have high membership in the outcome, and coverage assesses the extent to which the condition accounts for the outcome, in the presence of operational uncertainty in combination with organisational learning and Industry 4.0 and 5.0, technologies, and capabilities. With a high XY for solution 8 (0.876) and solution 7 (0.871), and a moderate to low XY, this indicates that the proposition is partially supported and that high performance depends on a large group of firms. However, it did not predict all cases. The same applies to solution 1.

4.5.2. Energy Stability and Security

For energy stability and security, the allotment of solution scores (truth table) and solutions for sufficient configurations of high sustained performance have also been developed. There were 11 solutions (Table 12). In these solutions, there are five solutions in

the presence of operational uncertainty due to energy stability and security, resulting in a high SPF when combined with security, Industry 4.0, and 5.0, technology capabilities, and organisational learning. Solution 6 had a high SPF in the presence of ESS when combined with RCAS, AI, and BDA in the absence of SPSI. Solution 8 was combined with RCAS, RPMR, and SPSI. The other solutions that would result in a high SPF are solutions 9, 10, and 11 in the presence of AI, and, sometimes, OLN and SPSI. There were no necessary conditions in the necessary condition analysis.

Table 12. 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”.

The XY plot shows that the proposition is partially supported by a high XY and a moderate to low $X \geq Y$ (Figure A1, plots d–h).

4.5.3. Operational Uncertainty Construct

SPSI and OLN were regarded as the core conditions, as they were present in both parsimonious and intermediate solutions and had a higher coverage and consistency (≥ 0.85). PEHS, AI, and ARVR, although they appeared in parsimonious and intermediate solutions, were still regarded as peripheral conditions because their solutions had a coverage < 0.50 or the coverage was < 0.85 . The results of the intermediate solution showed that the coverage of the solution was 0.686 and the consistency was 0.864 (Table 13).

Thus, the solution covers approximately 68.6% of the cases, and the consistency of the solution that accounted for the combination of conditions that consistently predicted the outcome was 86.4%. Only individual solutions with a coverage ≥ 0.2 and coverage ≥ 0.75 were reported. The solution $OPU2*OLN*\sim PEHS*AI*\sim ARVR$, denoted as solution 0, was used for a specific proposition. This proposition looked at the presence of operational uncertainty in combination with organisational learning and artificial intelligence. The XY plot is presented in Figure A1 plot i, showing the consistency with which the observations were plotted with $XY = 0.855$, while $X \geq Y = 0.448$. With a high moderate to low $X \geq Y = 0.448$, it indicates that the proposition that is partially supported is that a high performance depends on a large group of the firm; however, it does not predict all cases. The fsQCA results show that there are multiple configurations that can lead to a high sustained performance [99]. This supports

Proposition 2 that the combinations of OPU(2), IRT, and OLN conditions lead to a high or low sustained performance.

Table 13. Sufficient configurations of high sustained performance in the presence of operational uncertainty and Industry 4.0 and 5.0 technologies capabilities and organisational learning.

Outcome	Solution				
Configuration for High SPF	Configuration	1	2	3	
	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				

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”.

5. Discussion

The study developed a new integrated method, fuzzy-DEMATEL-PLS-SEM-fsQCA, for solutions for sustained performance during operational uncertainty in manufacturing. Fuzzy DEMATEL separated the nine dimensions into causes and effects [85]. This study identified the following 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. The PLS-SEM structural model showed 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 and sustained performance.

The rise in geopolitical tension enhances the operational uncertainty, with it actually migrating to a fully fledged geoeconomic confrontation. (Geoeconomic confrontation involves the use of economic tools to achieve strategic or political objectives, substituting or complementing military force.) The geopolitical risks have a significant impact on the global economic outlook, influencing supply chains, inflation, and financial markets [108]. The World Economic Forum [109] also advises that, “in a world already weakened by rising rivalries, unstable supply chains, and prolonged conflicts at risk of regional spillover, such confrontation carries systemic, deliberate, and far-reaching global consequences, increasing state fragility. The centrality of geoeconomic confrontation in the global risks landscape is not restricted to 2026, with respondents selecting it as the top risk over the two-year time horizon to 2028”. This highlights that this operational uncertainty dimension is top of the mind today and is expected to continue on the medium term.

Geopolitical tensions lead to supply chain disruption [110], increased costs [111], and regulatory changes that can restrict market access, forcing firms to adapt their supply chain networks to comply with new regulations or face penalties [112]. The fsQCA analysis shows solutions that are candidates for achieving a highly sustained performance in the presence of growing political tension. These include the use of AI or AI in combination with technologies that can enable flexible production (FPMC), mass customisation, and organisation learning conditions to manage geopolitical tension. The configurational analysis demonstrates that high sustained performance (SPF) can be achieved despite the presence of geopolitical tensions (GPT) when Industry 4.0 and 5.0 technologies’ capabilities are effectively combined. Specifically, configurations 1, 7, 8, and 10 reveal that the joint presence of scenario planning and supply chain integration (SPSI), and flexible production and mass customisation (FPMC), enables firms to proactively anticipate, absorb, and respond to geopolitical disruptions. Enhanced digital integration and visibility significantly reduce supply chain vulnerability under conditions of global uncertainty. Moreover, organisational learning (OLN) and root cause analysis with sustainable solutions (RCAS) function as dynamic capabilities that allow firms to continuously adapt and institutionalise lessons learned from disruptions. These capabilities strengthen resilience by preventing the recurrence of systemic failures during prolonged geopolitical stress.

This finding can also have implications for other African countries that face the same domino effect due to the dependence on countries that have heightened geopolitical tensions. Furthermore, operational uncertainties exist in terms of energy stability and security. The availability of a stable energy supply is closely related to economic and industrial sustainability. South African manufacturing industries remain among the most energy-intensive industries [113]. Unstable energy supply (load shedding) resulted in the manufacturing sector experiencing production halts and increased downtime, which compromises delivery schedules and overall productivity [114]. In some cases, load shedding led to a substantial increase in operational costs [115]. The results of the analysis yielded solutions that could 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 and AI. It can also be achieved in the presence of an ESS in combination with scenario planning and supply chain integration, root cause analysis, sustainable solutions, real-time monitoring and response, and organisational learning. There is also an option for quantum computing, but this might depend on the complexity of the problem, which requires root cause analysis. Similar to geopolitical

tensions, ESS may have implications for other countries that face the challenges of energy instability. This aligns with the relevance of this study for African countries.

In this study, a solution was also produced that looked at the presence of operational uncertainty in combination with organisational learning and artificial intelligence. This configuration is similar to some configurations proposed for other scenarios. AI, FPMC, and SPSI can potentially help manage operational uncertainty due to geopolitical tensions. SPSI and FPMC are mainly facilitated by 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. Augmented reality (AR) and virtual reality (VR) can be used for different training experiences and applications [116]. From an fsQCA perspective, these findings reflect the principle of equifinality, whereby multiple configurations of conditions lead to the same outcome of high SPF, even in the presence of GPT or ESS [31]. Thus, the synergistic bundling of Industry 4.0 and 5.0 technologies and capabilities offsets geopolitical risk, enabling firms to sustain a superior performance rather than succumb to external volatility.

The South Africa Manufacturing Analysis by PwC [117] highlights the steps the manufacturing firm can implement to improve its business, including strengthening the supply chain with IoT, AI, and, specifically, sensors, robotics, and decision intelligence systems. These assertions are in agreement with the solutions from fsQCA for sustained performance during a time of growing geopolitical tensions, which are combinations of Industry 4.0 and 5.0 technologies, and organisational learning. Against this backdrop, a framework was developed to provide the results of the configuration model (Figure 5).

This starts with the existence of operational uncertainty, showing how the associated dimensions influence manufacturing operations from supply chain disruption through an increase in the cost of production and 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 led to operational improvements and sustained high performance with particular configurations. Fuzzy-DEMATEL is a useful hybrid approach that integrates both qualitative and quantitative data and leverages fuzzy logic to handle inherent uncertainty and subjectivity in qualitative assessments [87]. The research method used in the present study obtained qualitative evaluations from experts, which were then integrated with quantitative data to form a comprehensive analytical framework [118]. Thus, this approach considers the recommendation of Miller [119] to combine quantitative and qualitative analyses and Greckhamer et al. [59] to build conceptually meaningful and empirically configurational theory.

The theoretical perspective subscribes to the same foundational core tenets of causal asymmetry, conjunctural causation, and equifinality [120]. The new wave of research directly focuses on causal complexity [29], which enables researchers to more adequately theorise and empirically examine causal complexity; this expectation is similar to the neo-configuration theory. Causal asymmetry was assumed to test the overall operational uncertainty in the 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 an energy stability and security-based model that would lead to sustained high performance. There is evidence of emergence tenets based on the structure and levels of operational uncertainty. This study postulates that there is a need for an additional tenet, an emergent core tenet, in the neo-configurational theory. It is evident from the empirical analysis that operational certainty has multiple dimensions. This complex phenomenon can be understood through the interplay between multiple

causal dimensions rather than isolating single mechanisms. This tenet is mainly associated with complexity theory [121]. However, it explains that emergence occurs when the system properties or levels of the complex firms are generated by agent self-organisation. This is especially relevant because emergence and causality are interconnected, with new causality arising at higher levels of abstraction that cannot be attributed to individual properties [122]. Emergent change, which is based on Industry 4.0 and 5.0 technologies, and organisational learning, can generally arise in response to external environment alterations, which can be diverse. Emergent changes enable firms to maintain adaptability and responsiveness to unplanned or unexpected changes. As such, this theoretical perspective subscribes to the core tenets of configurational theory and the emergent tenet of complexity theory.

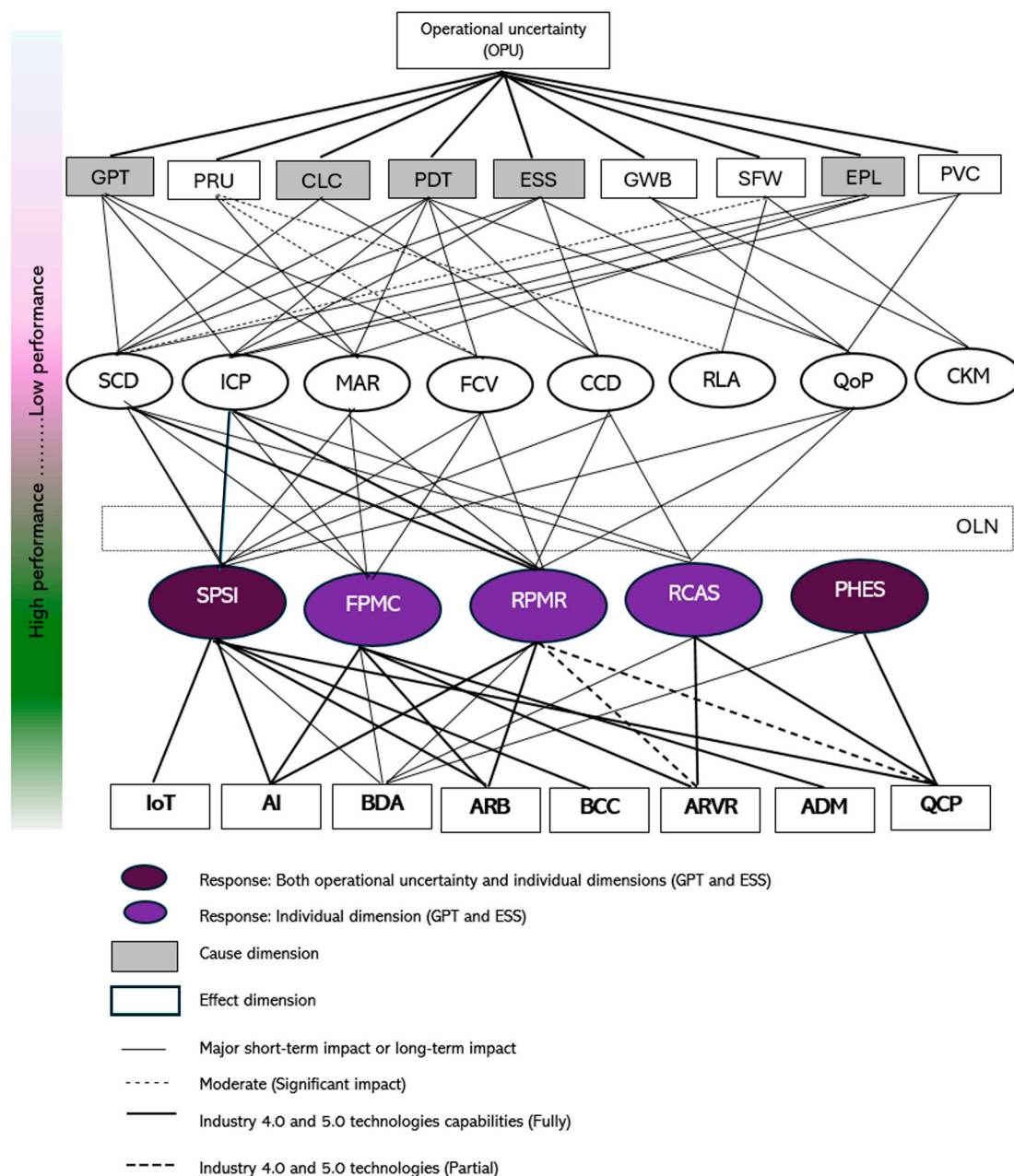


Figure 5. Framework of analysis of operational uncertainty.

6. Managerial Implications

The study provides actionable managerial implications for managing operational uncertainty within the firm context. First, under high geopolitical and trade uncertainty

(e.g., sanctions, tariffs, and regional conflicts), managers should prioritise SPSI as a core condition, supported by RPMR. Practically, this means investing in multi-tier supplier visibility platforms, digital twins for scenario simulation, and contingency routing strategies. Firms should institutionalise the ‘geopolitical stress test’ of supply chains at least annually to prevent disruptions. Secondly, with demand volatility and market fragmentation, firms facing unstable customer demand should emphasise FPMC as a core capability, enabling rapid product reconfiguration and localisation. Actionable steps include modular product architectures, postponement strategies, and digitally enabled mass customisation cells that allow fast switching between variants without cost penalties. Third, where internal process reliability is the main challenge, RPMR combined with RCAS should be prioritised. Managers should deploy real-time dashboards linked to automated alerts and embed structured root cause routines to ensure disruptions lead to permanent system improvements rather than temporary fixes. Fourth, in environments characterised by repeated shocks, OLN becomes a critical peripheral-to-core capability. Managers should formalise post-disruption learning loops, cross-functional knowledge repositories, and training programmes that translate crisis responses into standard operating procedures, thereby building long-term dynamic capabilities. Lastly, managers should avoid one-size-fits-all solutions. The presence of multiple high-SPF configurations (1, 7, 8, and 10) indicates that firms can choose resilience pathways aligned with their context, as long as critical Industry 4.0/5.0 technologies’ capabilities are bundled coherently rather than implemented in isolation.

7. Theoretical Implications, Limitations, and Directions for Future Research

This study advances configuration theory and a new integrated methodology (fuzzy-DEMATEL-PLS-SEM-fsQCA) to develop solutions for sustained performance during operational uncertainty in manufacturing. This research offers valuable information to advance the subject, make meaningful changes in day-to-day manufacturing operations, and promote practical, real-world problem solving. This study had several limitations that should be highlighted. Industry 4.0 and 5.0 technologies were not exhaustive. This study acknowledges that other integrated 4.0, 5.0, and/or individual technology extensions form smart factories in manufacturing that can be used to manage operational uncertainty. In addition, although fsQCA partially advanced the theory, it did not fully advance the theory, as not all cases were above the consistency above 0.80. This study should serve as a basis for further research on managing operational uncertainty with Industry 4.0 and 5.0 technologies. More research is required to manage operational uncertainty using technology. It can include research from BRICS+ partner countries such as China [123–125] and India [126], as they are advanced in Industry 4.0 and 5.0 technologies, and integration to manufacturing to improve efficiency and competitiveness. This will help to obtain more information and improve the generalisability of the findings to other regions, especially developed economies or other African contexts with different infrastructural and regulatory environments. Furthermore, the outcomes from the other setting help to further validate the proposed framework. This, together with practical implementation, will strengthen the framework, its applicability, and operability.

8. Conclusions

The study concludes that the growing geopolitical tension, the change in consumer behaviour driven by the cost of living, pandemic turbulence, lack of energy stability and security, and the entrenchment power of large firms are causal dimensions of operational uncertainty. These causal dimensions were used for the PLS-SEM and fsQCA analysis,

and the results showed a significant negative relationship between the two dimensions, growing political tension and energy stability, and security uncertainty with sustained performance. Industry 4.0 and 5.0 technologies with capabilities for scenario planning and supply chain integration, flexible production and mass customisation, real-time system and process monitoring and response, root cause analysis, and sustainable solutions, can manage operational uncertainty. These technologies include artificial intelligence, the Internet of Things, big data analytics, and, to a lesser extent, advanced robotics, blockchain, and augmented and virtual reality.

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Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
ARS	Advanced robotics and robotic systems
AR/VR	Augmented and virtual reality
BDA	Big data analytics
BC	Blockchain
CLC	Change in cost-of-living-driven consumer behaviour change
DEMATEL	Decision-making trial and evaluation laboratory
EPL	Entrenchment power of large firms
ESS	Energy stability and security
FIMIX	Finite mixture
FPMC	Flexible production and mass customisation
fsQCA	Fuzzy set qualitative comparative analysis
GDP	Gross domestic product (GDP)
GPT	Geopolitical tension
GWB	Generational work behaviour and ethics
ICC	Intraclass Correlation Coefficient
IRT	Industrial revolution technologies
OLN	Organisational learning
PCV	Process capability and variations
PLS-SEM	Structural equation modelling partial least squares
PDT	Pandemic turbulence
PEHS	Protective ecosystem (human and system)
PRU	Policy and regulatory uncertainty
QC	Quantum computing
RCAS	Root cause analysis and sustainable solutions

RPMR	Real-time system and process monitoring and response
SPSI	Scenario planning and supply chain integration
SFW	Skills for future industrial work

Appendix A. XY Plots of fsQCA for Solutions in the Presence of GPT, ESS, and OPU

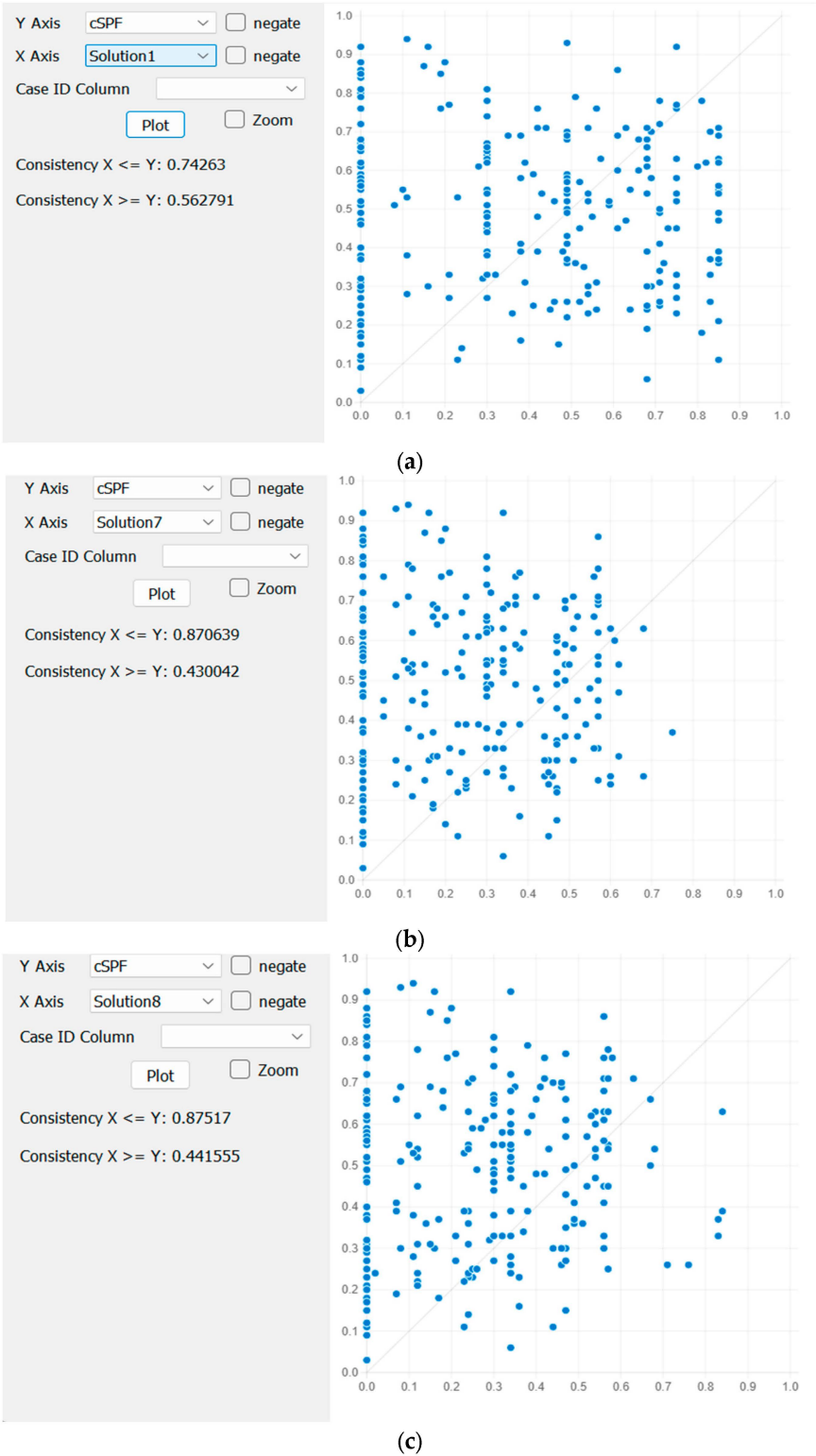
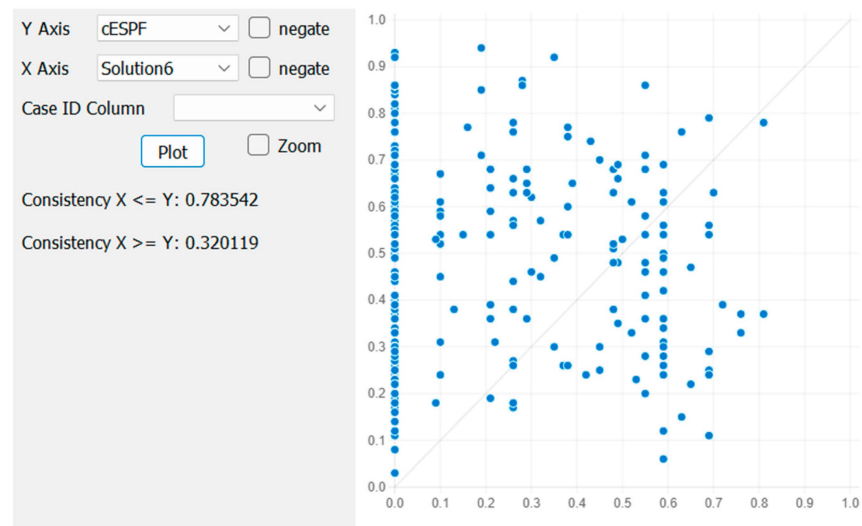
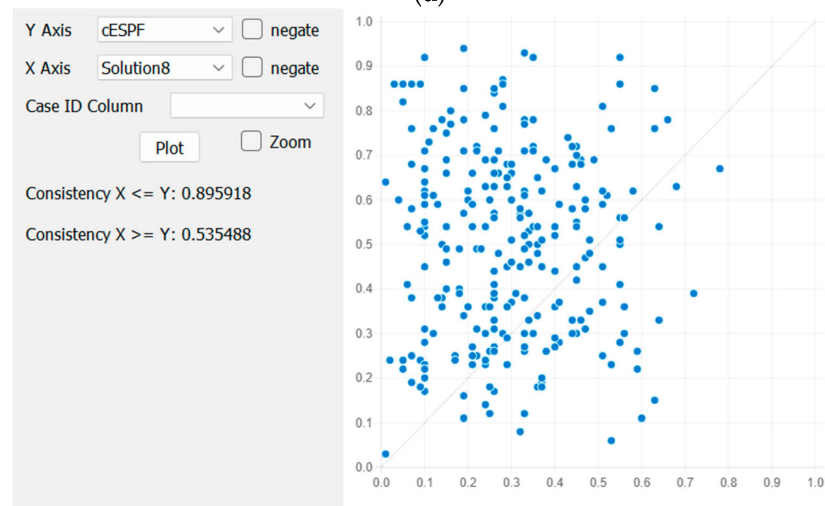


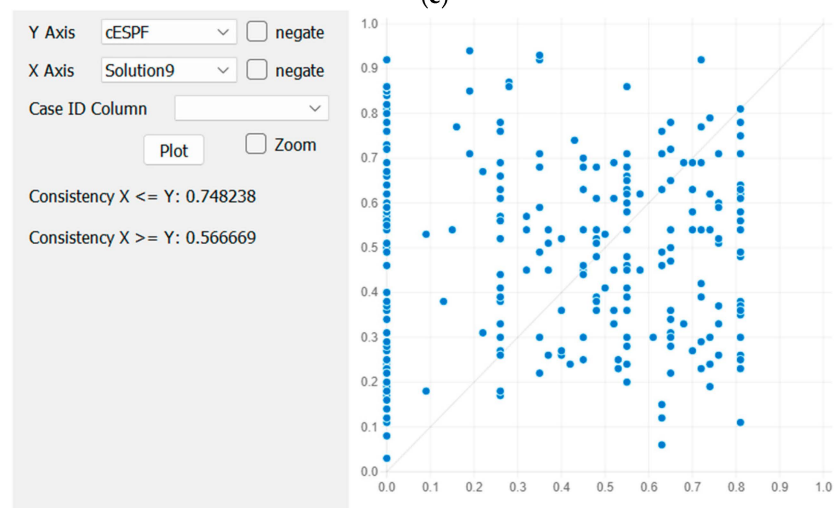
Figure A1. Cont.



(d)



(e)



(f)

Figure A1. Cont.

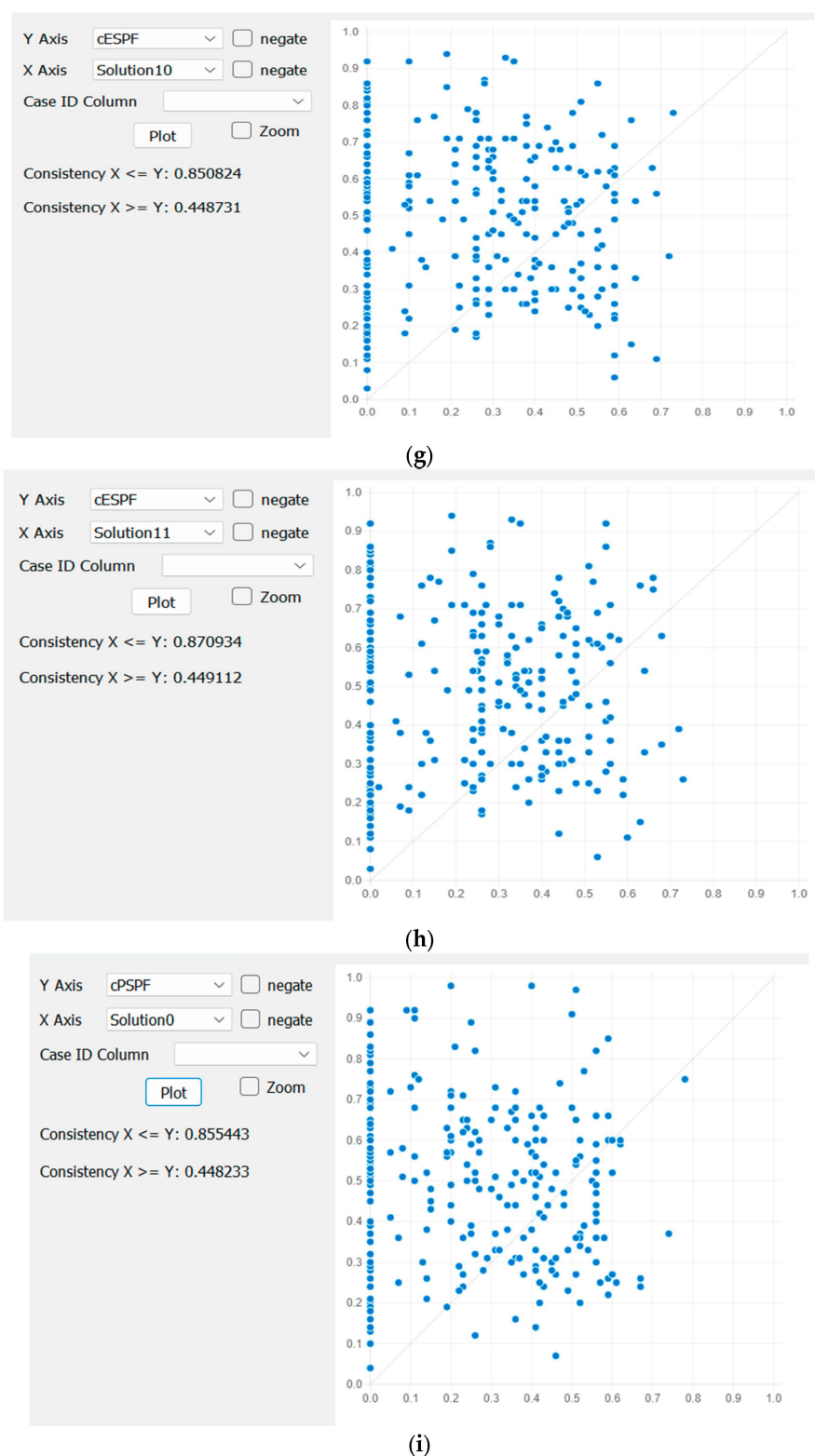


Figure A1. XY Plots of fsQCA for solutions.

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