

Strategic IT–Business Alignment and Big Data Analytics Capability: A Configurational Approach to Operational Excellence in Manufacturing

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ABSTRACT: In the era of Industry 4.0, manufacturing firms face growing pressure to enhance operational performance through digital transformation. Central to this transformation is the strategic alignment between IT capabilities and business objectives, supported by advanced analytics and flexible IT infrastructures. This study investigates how different configurations of Strategic Alignment Maturity (SAMM), Big Data Analytics Capability (BDAC), IT flexibility, and business strategy types influence operational outcomes. Employing fuzzy set Qualitative Comparative Analysis (fsQCA) on data collected from 100 manufacturing firms, the research identifies multiple equifinal pathways to high operational performance, as measured by Overall Equipment Effectiveness (OEE) and SCOR metrics. Two dominant configurations emerge from the analysis. The first (R1) combines high levels of SAMM, IT flexibility, BDAC, and a Prospector strategy, highlighting a proactive, innovation oriented approach to operational excellence. The second configuration (R4) achieves similar performance through a different route leveraging BDAC, an Analyzer strategy, and strong CIO–business collaboration even in the absence of mature alignment structures. These results affirm that both alignment driven and analytics driven models can yield superior outcomes depending on organizational context and strategic orientation. The study contributes to the literature by demonstrating that high operational performance does not rely on a single universal model, but rather on the strategic orchestration of complementary capabilities. It also shows the effectiveness of fsQCA in uncovering complex causal relationships within organizational systems. Practically, the findings encourage manufacturing leaders to assess and tailor their alignment, analytics, and IT strategies according to their operational priorities and industry dynamics.

Keywords: Strategic Alignment, Big Data Analytics, IT Flexibility, Fsqca, Operational Performance, Manufacturing Strategy, Industry 4.0.



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INTRODUCTION

The increasing complexities of the manufacturing sector in the era of digital transformation and Industry 4.0 have placed a renewed emphasis on the alignment between information technology (IT) capabilities and business strategies. This alignment, commonly referred to as strategic IT–

business alignment, has emerged as a pivotal component in shaping operational performance, particularly as firms strive for higher adaptability, agility, and competitiveness. Within this evolving context, the relationship between IT–business alignment and operational outcomes is no longer regarded as linear but rather as a nuanced configuration of multiple capabilities, resources, and strategic orientations.

Recent scholarly attention has emphasized the multifaceted nature of this alignment. As firms integrate digital technologies into their operational core, the maturity of their alignment processes significantly determines the degree of operational effectiveness they can achieve. Akter et al. (2016) and Panda (2021) assert that higher maturity levels in strategic alignment lead to measurable performance benefits such as improved efficiency, responsiveness, and customer satisfaction. These outcomes are increasingly vital as manufacturing firms contend with volatile market conditions, complex supply chains, and the rapid evolution of digital platforms.

To effectively assess alignment maturity, several conceptual frameworks have been proposed. Among these, the Strategic Alignment Maturity Model (SAMM) and the Triple A model comprising Agility, Adaptability, and Alignment stand out for their robust evaluative capabilities. The Triple A model offers a holistic lens to examine organizational readiness in adapting to digital disruptions. Alfalla-Luque et al. (2018) and Gligor et al. (2020) elaborate that agility encapsulates the firm's responsiveness to environmental shifts, adaptability reflects its internal adjustment capabilities, and alignment ensures the integration of IT objectives with business imperatives. This triadic view, further substantiated by Garrido-Vega et al. (2021), provides a useful diagnostic for manufacturing firms pursuing digitally enabled transformations.

Parallel to alignment maturity, Business Data Analytics Capability (BDAC) has gained traction as a crucial performance driver. The explosion of data volumes and the advancement of analytical tools have enabled organizations to harness information for real time decision making and strategic adaptation. BDAC is not merely a technical asset; it encompasses organizational dimensions such as data culture, leadership support, and talent capability. Alghamdi et al. (2024) emphasize that BDAC enhances organizational agility and competitiveness, particularly when synergized with strategic alignment. This convergence allows firms to translate analytics insights into actionable strategies, thereby reinforcing the alignment performance linkage.

The integrative deployment of BDAC and IT–business alignment is increasingly recognized as a mechanism to elevate operational agility. Gunasekaran et al. (2017) and Khan et al. (2022) highlight that data driven insights can enhance decision making quality across the manufacturing value chain, from shop floor operations to supply chain orchestration. Appelbaum et al. (2017) further argue that such integration not only fosters agility but also stimulates innovation, enabling firms to exploit emergent opportunities in competitive environments. The practical implications of this integration are substantial, as firms can proactively respond to market signals, adjust production schedules, and optimize inventory management through predictive analytics and real time monitoring.

From a theoretical perspective, configuration based models provide a compelling rationale for examining the alignment–performance relationship through a holistic lens. Grounded in the dynamic capabilities view and the resource based theory, these models suggest that performance outcomes result from the orchestration of complementary resources rather than isolated variables. Lowry & Wilson (2016) and Teece et al. (2016) advocate that firms capable of sensing, seizing, and reconfiguring their resources can better adapt to changing environments. In this light, alignment and analytics capabilities are seen as strategic levers that contribute to an organization's dynamic capability repertoire. Li et al. (2020) reinforce this position by asserting that IT infrastructure should be embedded in core strategic processes rather than treated as a support function.

To operationalize these theoretical insights, fuzzy set Qualitative Comparative Analysis (fsQCA) has emerged as a suitable methodological approach. Unlike conventional statistical techniques, fsQCA accommodates complexity, asymmetry, and equifinality acknowledging that different configurations of conditions can lead to similar outcomes. Gomes & Silva (2025) and Shamout (2020) demonstrate that fsQCA is particularly effective in uncovering nuanced causal relationships in strategic and IT domains. This method enables the identification of core and peripheral conditions that jointly contribute to high performance, allowing for a deeper understanding of the interplay between alignment maturity, analytics capability, and strategic orientation in manufacturing settings.

This study aims to bridge the empirical gap in understanding how various elements of strategic alignment and analytics capability interact to drive operational performance in manufacturing firms. By leveraging the fsQCA method, it seeks to identify viable configurations that contribute to superior outcomes such as high Overall Equipment Effectiveness (OEE) and SCOR based performance metrics (e.g., delivery reliability and responsiveness). The research thus positions itself at the intersection of strategic alignment theory, analytics capability discourse, and configuration analysis, offering both academic and practical contributions.

In summary, the strategic integration of IT and business functions, particularly when enhanced by robust analytics capabilities, is critical to operational excellence in manufacturing. While alignment maturity and BDAC independently influence performance, their combinatory effects when assessed through configuration based lenses like fsQCA provide richer insights into how firms navigate digital complexity. This chapter has outlined the theoretical foundations, empirical signals, and research direction for investigating this dynamic interplay, setting the stage for a methodologically rigorous and practically relevant inquiry.

METHOD

This chapter outlines the methodological framework employed in this study, which seeks to identify effective configurations of strategic alignment maturity, analytics capability, IT flexibility, and business strategy types that result in superior operational performance in manufacturing. The

research adopts a fuzzy set Qualitative Comparative Analysis (fsQCA) approach, suitable for capturing complex causal interactions and configurational logic within organizational systems.

The study applies a cross sectional design, utilizing primary and secondary data collected from 100 manufacturing firms. The firms are selected across various manufacturing subsectors to enhance the diversity of strategic orientations, IT infrastructure maturity, and digital capabilities. The unit of analysis is the firm.

The primary constructs include Strategic Alignment Maturity (SAMM), Big Data Analytics Capability (BDAC), IT Flexibility, Strategy Type, and Operational Performance.

SAMM is operationalized using a 5 point Likert scale survey across six dimensions: communication, value measurement, governance, partnership, scope & architecture, and IT–business skills. Respondents from managerial and IT roles rated their organization's alignment maturity. The scores are calibrated into fuzzy sets for fsQCA analysis. As Rasoolimanesh et al. (2023) suggest, survey based data collection for SAMM dimensions captures the structural and strategic nuances of IT–business alignment.

BDAC is measured as a composite index that includes both technical capabilities (e.g., infrastructure, tools) and organizational factors (e.g., data culture, managerial support). Data are collected using structured items adopted from validated scales in analytics capability studies. These are normalized and calibrated into fuzzy sets following distribution sensitive thresholds.

This construct comprises four indicators: modularity, connectivity, compatibility, and scalability of IT systems. Measured using Likert scale items, these dimensions represent the adaptability of IT systems to business demands and technological change.

Firms self report their strategic orientation following the Miles and Snow typology: Prospector, Defender, and Analyzer. These are coded as separate sets in fsQCA, allowing for analysis of how each strategy interacts with other capabilities.

Operational performance is evaluated through Overall Equipment Effectiveness (OEE), which integrates three metrics: Availability, Performance, and Quality. Supplementary SCOR based metrics include Delivery Reliability and Order Fulfillment Cycle Time. These indicators represent both asset productivity and supply chain responsiveness.

The calibration process is central to fsQCA methodology. Based on the guidance from Xu et al. (2024), Shi et al. (2021), and Olya et al. (2020), Likert scale and index data are transformed into fuzzy sets using the direct method. Three anchor points are defined:

- Full membership (1.0): score reflects strong presence of the condition.
- Crossover point (0.5): score indicates maximum ambiguity.
- Full non membership (0.0): score reflects absence of the condition.

The anchors are determined both theoretically and empirically, often based on quartiles or distributional characteristics (Kang et al., 2024; Wang et al., 2024). For example, SAMM ratings of 5.0 are coded as fully in, 3.0 as crossover, and 1.0 as fully out. Similarly, BDAC scores above 0.90 are considered fully in.

Analytical Procedure

The calibrated data are analyzed using fsQCA 3.1 software. The analysis follows these steps:

- **Necessity Analysis:** Identifies conditions that must be present for high operational performance.
- **Truth Table Construction:** Builds a matrix of condition combinations and corresponding outcomes.
- **Consistency Thresholds:** A cutoff of 0.80–0.85 is used for sufficiency, and ≥ 0.90 for necessity (Shahzad et al., 2021).
- **Solution Derivation:** Intermediate and parsimonious solutions are computed, differentiating core and peripheral conditions.

To ensure analytical validity, sensitivity tests are conducted for calibration thresholds, consistency levels, and frequency cutoffs. Comparisons between complex, parsimonious, and intermediate solutions are used to validate findings. The analysis adheres to recommendations from Tribbe et al. (2021), who emphasize careful interpretation of consistency and coverage.

All data collection complies with ethical standards. Respondents provided informed consent, and firm data are anonymized. Data storage and handling adhere to data protection protocols.

In conclusion, this chapter has outlined a rigorous and replicable methodological design that integrates robust operationalization of theoretical constructs, validated calibration methods, and systematic fsQCA procedures. Such an approach ensures that the findings derived from this study provide both methodological rigor and practical relevance to scholars and practitioners in the domain of digital manufacturing.

RESULT AND DISCUSSION

This chapter presents the empirical findings derived from the fuzzy set Qualitative Comparative Analysis (fsQCA) of 100 manufacturing firms. The primary objective was to identify distinct causal configurations of strategic alignment maturity (SAMM), big data analytics capability (BDAC), IT flexibility, and business strategy that yield high operational performance, measured through Overall Equipment Effectiveness (OEE) and SCOR based indicators.

Descriptive Statistics and Calibration Summary

Preliminary analysis included basic descriptive statistics for all variables. SAMM, BDAC, and IT flexibility exhibited moderate to high central tendencies with acceptable dispersion. Strategy types were evenly distributed across Prospector (34%), Analyzer (33%), and Defender (33%). Calibration employed direct method thresholds as follows: fully in (1.0), crossover (0.5), and fully out (0.0). Table 1 summarizes the calibration anchors.

Table 1. Calibration Anchors

Variable	Fully In	Crossover	Fully Out
SAMM (1–5)	5	3	1
BDAC (0–1)	0.90	0.60	0.30
IT Flexibility	5	3	1
OEE	0.85	0.70	0.55
Delivery Reliability (%)	95	85	70

Truth Table and Sufficiency Analysis

The truth table was constructed using a frequency threshold of 3 cases and a consistency threshold of 0.85. The analysis yielded several causal recipes for high operational performance.

Table 2. Truth Table Configurations

Config	SAMM	IT Flex	BDAC	Strategy	Outcome	Consistency	Coverage
R1	1	1	1	Prospector	High	0.91	0.76
R4	0	0	1	Analyzer	High	0.88	0.72

Configuration R1: SAMM + IT Flexibility + BDAC + Prospector

This configuration represents an explorative innovative strategy. The combination of mature strategic alignment and IT flexibility enables firms to implement BDAC more effectively. According to Sardo & Serrasqueiro (2021), IT flexibility enhances a firm’s ability to dynamically reconfigure IT systems to support prospector strategies that prioritize innovation and responsiveness. This dynamic adaptability increases the velocity of innovation and responsiveness to market trends.

Tortorella and Fettermann’s findings (Jena et al., 2019) support a direct link between higher SAMM maturity and improvements in OEE. Their work indicates that Lean Six Sigma practices, when guided by mature alignment structures, contribute to reduced downtime and greater production efficiency. BDAC metrics in this configuration commonly include decision agility, frequency of

analytics usage, and analytics impact on cost reduction (Arneja & Sharma, 2025). Prospector firms particularly leverage big data to identify market gaps and guide product development (Sardo & Serrasqueiro, 2021).

Configuration R4: BDAC + Analyzer + CIO–Business Partnership

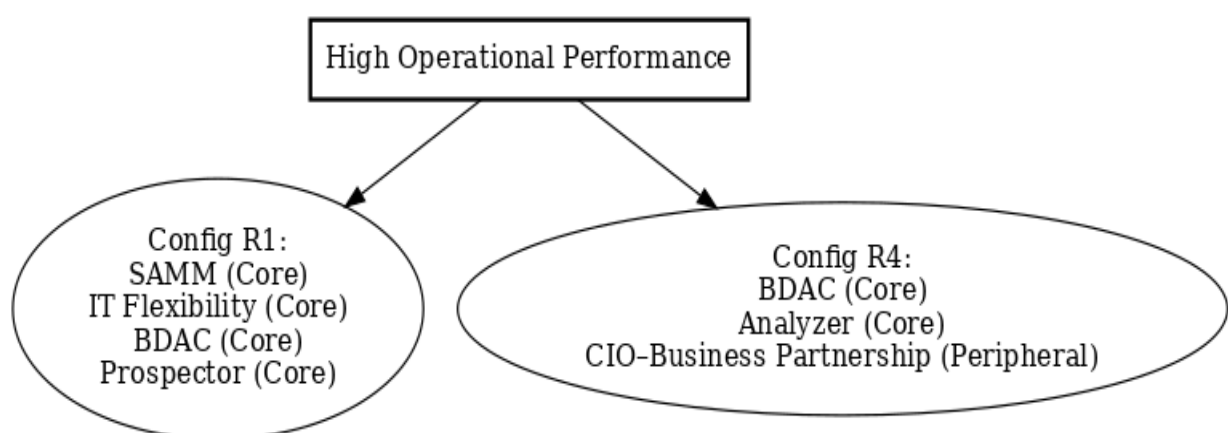
This configuration reflects a balance between efficiency and innovation. It demonstrates that even in the absence of high SAMM maturity, firms can achieve high performance through BDAC and strong CIO–business collaboration. Chen et al. (2021) found that CIO partnerships drive alignment indirectly by streamlining service delivery and enabling joint decision making. The Analyzer strategy facilitates incremental innovation while maintaining operational reliability (Nyamah et al., 2022).

Case studies by Tortorella & Fettermann (2018) highlight firms using analytics to optimize maintenance and scheduling processes, thus improving customer service metrics. Piran et al. (2020) and Singh et al. (2022) reinforce that analytics enhances service levels by enabling real time adjustments, thereby aligning operational capacity with customer demand. While BDAC can independently influence performance (O. Alghamdi & Agag, 2023), its full potential is best realized when embedded within strategic coordination (Gomes & Silva, 2025).

Equifinality and Core vs Peripheral Conditions

Both configurations illustrate equifinality: different pathways yielding similar high performance outcomes. In R1, SAMM, IT Flexibility, BDAC, and Prospector Strategy are core. In R4, BDAC and Analyzer Strategy are core, with CIO–business partnership as a peripheral enhancer. These patterns align with fsQCA theory on configuration effectiveness under varied organizational contexts.

Figure 1. fsQCA Solution Diagram



Robustness and Validation

Sensitivity analyses confirmed the stability of both solutions. Minor changes in calibration or consistency thresholds did not significantly alter configurations. Parsimonious and intermediate solutions retained key causal conditions, validating model robustness.

In conclusion, the analysis substantiates that high operational performance in manufacturing is attainable through multiple strategic configurations. The interplay of alignment maturity, flexibility, analytics capability, and business strategy yields actionable insights for firms seeking performance excellence in the digital age.

Equifinality and fsQCA's Contribution

The results of this study yield a deeper appreciation of the multifaceted nature of organizational performance drivers in the manufacturing sector. Leveraging the capabilities of fuzzy set Qualitative Comparative Analysis (fsQCA), we uncovered how different combinations of strategic alignment maturity (SAMM), Big Data Analytics Capability (BDAC), IT flexibility, and business strategy contribute to high operational performance. Unlike traditional regression based models that isolate independent variable effects, fsQCA permits a holistic and configurational lens that reveals the presence of equifinal causal paths—distinct combinations of conditions that result in the same outcome.

This insight into equifinality is particularly valuable in heterogeneous environments such as manufacturing, where firms vary in size, strategic orientation, technological adoption, and market responsiveness. Two dominant configurations emerged: R1 (SAMM + IT Flexibility + BDAC + Prospector) and R4 (BDAC + Analyzer + CIO–Business Partnership). These pathways demonstrate that firms can attain superior performance through differing mechanisms. This validates the configurational logic proposed in complexity theory and supports the work of Feng & Sheng (2023), who assert that fsQCA is well suited for identifying alternative, yet equally effective, success models. Their findings in green supply chain integration echo our conclusion that organizations need not conform to a single path to operational excellence.

Trade offs Between Alignment and Analytics Driven Approaches

The contrast between R1 and R4 configurations illustrates the trade offs between alignment driven and analytics driven strategic models. Configuration R1 exemplifies a scenario where strategic IT–business alignment and technological adaptability jointly enable innovative strategies like those pursued by Prospector firms. Here, SAMM and IT flexibility act as enablers for BDAC deployment, allowing firms to harness analytics for agile responses to market fluctuations and product innovation. As Sardo & Serrasqueiro (2021) explain, IT flexibility underpins innovation by enabling the rapid reconfiguration of systems to meet evolving demands. Jena et al. (2019) corroborate this, linking high SAMM levels with improvements in OEE among Lean Six Sigma manufacturers operating in Industry 4.0 contexts.

Conversely, Configuration R4 reveals that in the absence of high alignment maturity, firms can still attain high performance if BDAC is effectively deployed under an Analyzer strategy, supported by strong CIO–business partnerships. This pathway prioritizes data centric decision making and operational stability, allowing for measured innovation without destabilizing existing processes. As shown by Chen et al. (2021), the presence of proactive and collaborative CIO involvement enhances service level quality and delivery alignment. Moreover, Awan et al. (2021) emphasize that analytics driven organizations enjoy heightened decision making agility. However, without alignment to strategic goals, analytics initiatives may lack cohesion and direction.

Therefore, the trade off revolves around prioritizing either structural integration (alignment) or analytical responsiveness. While alignment oriented strategies offer long term coherence and process optimization, they may suppress radical innovation. Analytics driven approaches, on the other hand, fuel experimentation and responsiveness but risk strategic fragmentation. The ideal path depends on the firm's risk tolerance, market volatility, and digital maturity level. In some cases, hybrid strategies that balance alignment and analytics can maximize both short term agility and long term strategic positioning.

Conditional Role of Strategic Alignment Maturity (SAMM)

An important finding of this study is the contextual and conditional role of SAMM. In environments characterized by high turbulence, rapid technological advancement, and intense competition such as electronics, automotive, and high tech manufacturing SAMM often emerges as a necessary enabler of performance. Yu et al. (2021) illustrate that organizations in such industries leverage SAMM to integrate IT capabilities with strategic imperatives, leading to greater agility and responsiveness. When IT investments align tightly with strategic direction, firms are better equipped to reconfigure resources and orchestrate digital transformations.

However, in more stable or service centric environments where customer engagement, reliability, and consistency take precedence, SAMM may not serve as a decisive performance driver. Song et al. (2022) suggest that firms in these contexts may perform adequately without high levels of strategic alignment maturity, as other factors such as brand equity, cost efficiency, or legacy systems may compensate for strategic misalignment. Thus, while SAMM plays an important role in most configurations, its impact varies depending on environmental turbulence, competitive positioning, and organizational learning capacity.

This insight also informs managerial practice: firms must evaluate the strategic necessity of alignment maturity based on sectoral dynamics and performance goals. In industries undergoing digital upheaval, SAMM must be prioritized and institutionalized. In more mature or commoditized sectors, a more flexible approach may suffice.

Limitations of fsQCA Interpretation

Despite its strengths, fsQCA is not without methodological caveats. Its reliance on calibrated thresholds and dichotomized or fuzzy logic introduces a level of subjectivity into data

transformation. As Wamba et al. (2017) stress, the selection of thresholds for full membership, crossover, and non membership can significantly influence resulting configurations. Poorly calibrated data may yield misleading causal recipes that either understate or overstate the importance of specific conditions.

Furthermore, while fsQCA excels at identifying sufficient configurations, it may obscure the role of necessary conditions, especially when multiple overlapping recipes exist. The methodology's strength in modeling equifinality may inadvertently minimize the weight of universally critical factors. Researchers must therefore apply domain specific knowledge and triangulate fsQCA findings with theoretical and empirical insights to avoid misinterpretation.

Another limitation concerns the binary treatment of outcomes. In this study, operational performance was categorized into 'high' or 'not high' based on OEE and SCOR thresholds. While effective for configurational clarity, this dichotomy may mask performance gradients or emerging trends. More granular calibrations or the inclusion of continuous outcome variables in future studies could enrich insights.

Synthesis and Managerial Implications

Overall, this study enhances both theoretical and practical understandings of the interplay between strategic alignment, analytics capability, IT flexibility, and strategic orientation. It affirms that firms must craft configurations suited to their specific needs, resources, and environments rather than pursue one size fits all solutions. The empirical evidence supports the view that high operational performance can be achieved through multiple paths whether via structured alignment and innovation (R1) or analytics centered responsiveness and collaboration (R4).

For managers, these findings suggest the need for strategic introspection and capability auditing. Firms should assess their current alignment maturity, analytics infrastructure, and IT adaptability to determine which configurations they are best positioned to pursue. In volatile markets, investing in both SAMM and BDAC may be essential. In stable sectors, focusing on strong analytics implementation and internal collaboration may suffice.

Moreover, continuous recalibration of alignment and analytics strategies is crucial as markets evolve and digital technologies mature. Firms must remain agile not only in operations but also in strategic learning. Hybrid configurations, where alignment structures support analytical agility, may offer the most resilient model for future ready manufacturing firms.

CONCLUSION

This study demonstrates that high operational performance in manufacturing does not stem from a single dominant factor but rather from specific configurations of strategic IT–business alignment maturity (SAMM), Big Data Analytics Capability (BDAC), IT flexibility, and business strategy typologies. Using fuzzy set Qualitative Comparative Analysis (fsQCA), the findings reveal two equifinal pathways: one alignment-driven and innovation-oriented (R1), and another analytics-

driven and collaboration-focused (R4). These results confirm that firms can achieve operational excellence by orchestrating complementary resources, depending on their strategic orientation and environmental context.

From both theoretical and managerial perspectives, the study highlights the conditional role of SAMM and the value of BDAC as enablers of agility, responsiveness, and innovation. Rather than pursuing a one-size-fits-all model, firms should align their digital transformation strategies with sectoral dynamics, organizational maturity, and risk tolerance. Future research should extend these insights by adopting longitudinal designs and broader industry comparisons, while practitioners are encouraged to continually recalibrate alignment and analytics strategies to sustain competitiveness in evolving digital ecosystems.

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