

From analytics capability to performance: Data-driven decision making in U.S. FMCG small and medium enterprises

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Abstract

Small and medium enterprises (SMEs) in the United States fast-moving consumer goods (FMCG) sector face volatile demand and tight resources, yet little is known about how predictive analytics capability translates into organizational performance. Drawing on dynamic capabilities theory and organizational information processing theory, this study examines the effects of four capability dimensions (data quality and accessibility, analytics infrastructure, analytical skills and expertise, and predictive modelling capability) on financial forecasting accuracy, risk management effectiveness and operational efficiency. It also tests data-driven decision-making as a mediator and organizational analytics culture as a moderator. A face-to-face survey of 400 managers and decision makers in FMCG SMEs was analysed using partial least squares structural equation modelling, complemented by fuzzy set qualitative comparative analysis (fsQCA). All four capability dimensions had significant positive effects on the three outcomes (β from 0.108 to 0.239). Data driven decision making mediated the link between capability and performance (indirect $\beta = 0.067$, $p = 0.003$), while the direct effect was not significant. Analytics culture had a direct positive effect on performance ($\beta = 0.201$) but did not moderate the relationship between capability and performance. The fsQCA results showed that no single capability was necessary and that several combinations of capability, decision processes and culture were associated with high performance. The study offers evidence from an under-researched sector and proposes a conceptual framework to guide analytics adoption in FMCG SMEs.

Keywords: Predictive Analytics Capability, Data-Driven Decision-Making, Organizational Analytics Culture, Organizational Performance, FMCG SMEs, Dynamic Capabilities, Information Processing Theory, Partial Least Squares, Qualitative Comparative Analysis

JEL Classification: M15, L25, L81

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1. Introduction

Business processes, interactions among people, supply chains and trading activities have created a massive amount of digital information that has changed the nature of decision-making and competition for organizations today. In the business world, companies are turning more and more to sophisticated analytics tools to transform vast quantities of information into meaningful insights they can use to inform business decisions and optimize processes. One of the most significant advancements in this field is the use of predictive data analytics, which allows organizations to detect patterns, forecast future events and decisions based on predicted data instead of assumptions or intuition (Dhanekula, 2025). In today's competitive and rapidly changing market, predicting trends and reacting to new threats is a key skill for businesses to successfully survive and grow.

The U.S. Fast-Moving Consumer Goods (FMCG) industry is inherently competitive, with consumers' preferences shifting, demand shifting and changing, supply chain disruptions, high operating costs, and pressure to be more efficient. Small and medium enterprises (SMEs) in this industry are more likely to be disadvantaged compared to large companies, as they are usually resource constrained, have limited budgets and not as technologically capable as larger companies. Darboe (2026) states that SMEs make up a significant percentage of businesses and play a substantial role in creating jobs and economic activity in the US. Even though they are an important part of the economy, many SMEs still find themselves in a situation where they are unable to forecast accurately, manage risk effectively and make efficient operational plans, especially in an environment with a high level of uncertainty and rapid market change. Understanding what factors hinder SMEs from completely leveraging sophisticated digital technologies for strategic decision-making is crucial. Research into digital transformation of small businesses shows that financial, technological, human, and organizational resource limitation is a key factor that often prevents SMEs from fully utilising sophisticated digital technologies for strategic decision-making (McIlveene et al., 2026). The use of predictive data analytics has emerged as a possibility for SMEs to optimize their decision-making processes in recent times, with the support of new analytics technologies. These technologies enable businesses to process data from the past and present to forecast future trends in sales, stock, customer demand, financial performance, and operational risks (Fowowe & Adepapo, 2025). Predictive analytics is a powerful tool that can help organizations make better decisions, optimize resource allocation, minimize losses, and gain a competitive edge. In the same way, published findings from small business technology adoption research reveal that digital innovations can enhance operational efficiencies, customer engagement, transaction management and business growth when aligned to consumer expectations and the needs of the organization (Malone & Thomsen, 2025). However, it is found that the majority of SMEs are not able to fully utilize these capabilities because of poor data quality, lack of technology infrastructure, analytical skill, and organizational preparedness (Hazra, 2026). This means that the positive effects of using predictive analytics are not being felt equally by businesses. In that, numerous SMEs in the U.S are still in the experimentation phase with advanced

technologies due to a lack of capabilities and governance processes to turn technological investments into a lasting competitive edge (McIlveene et al., 2026). The aim of this study therefore, is to investigate the implementation and impact of predictive data analytics on organizational performance enhancement among SMEs in the FMCG industry in the United States. Specifically, the study seeks to:

- 1) assess the extent, effectiveness, and predominant applications of predictive data analytics among SMEs in the FMCG industry in the United States;
- 2) examine the influence of predictive data analytics capability on financial forecasting accuracy, risk management effectiveness, and operational efficiency among SMEs in the FMCG industry in the United States; and
- 3) examine the mediating role of data driven decision making and the moderating role of organizational analytics culture in the relationship between predictive data analytics capability and organizational performance enhancement among SMEs in the FMCG industry in the United States.

The novelty of this study stems from the integration of predictive data analytics capability, data driven decision making, organizational analytics culture, and organizational performance enhancement within a single framework specifically developed for FMCG SMEs in the United States. This study is different from the vast number of previous studies that focused on specific relationships, because it analyzes direct, mediating, and moderating relationships in the same empirical model. Another unique aspect of the work is the use of a second order conception of predictive data analytics capability, which includes data quality/accessibility, analytics infrastructure, analytical skills and expertise, and predictive modelling capability. Organizational performance improvement is analyzed as a multi-dimensional approach that includes financial forecasting accuracy, risk management effectiveness and operational efficiency. This holistic view offers a more complete picture of how resources for analytics are manifested in real business results. The study has found an appropriate need in the context of the current exigencies that require practical and empirical solutions, which can enlighten SMEs in the increasingly complex and data-oriented world of business. So many organisations are investing in analytics technologies without knowing what the organisation needs to be, do and have to implement the technology successfully. There is a shortage of evidence that can inform such investments within the context of FMCG SME. Therefore, empirical evidence is needed to provide the basis for better adoption of analytics, better decision quality and better organizational performance in this area. The study has implications for multiple stakeholders. SME owners and managers could perhaps find it helpful to expand their knowledge of the organizational capacity needed to get value from predictive analytics projects. The results can be utilized to build technology solutions that reflect the requirements and reality of small businesses. Another group of users can be government and other policy & business support institutions that can also leverage the evidence to drive digital

transformation and analytics readiness among SMEs. Academically, the study builds on the existing research base concerning predictive analytics capability and organizational performance by adding to the very limited research done in an under-researched industry. The remaining sections of this paper present the literature review, materials and methods of the study, which describes the research design, data collection procedures, measurement of study variables, and analytical techniques employed, including structural equation modelling and fuzzy set qualitative comparative analysis. The results and discussion sections come next, showing the empirical results and discussing them in light of the literature. Following these, recommendations are made for practitioners, policy-makers and other stakeholders. The last section proposes an evidence-based roadmap that can help FMCG SMEs improve their capability in predictive data analytics and boost their organization's performance outcomes.

2. Literature Review

2.1 Predictive Data Analytics Capability

Predictive Data Analytics Capability refers to an organization's ability to use data, analytical technologies, human expertise, and predictive models to generate information about future events and support organizational action. Recent literature increasingly treats analytics capability as a combination of complementary organizational resources rather than simply possession of analytical software. Vesterinen et al. (2024) conceptualize big data analytics capability through technological resources, analytical infrastructure, personnel skills, and organizational resources, emphasizing that these resources must work together to generate business value. Similarly, recent research on analytics capabilities highlights data management, analytical technologies, employee skills, and organizational resources as important foundations for effective analytics use. Orero-Blat et al. (2025) further demonstrate that analytics capability enables SMEs to adapt to changing markets and improve performance when supported by appropriate organizational conditions. Previous studies have therefore operationalized analytics capability through measures of data quality, technological infrastructure, analytical expertise, and the ability to develop and apply analytical models. In the present study, PDAC represents the firm's overall capacity to acquire and prepare reliable data, maintain suitable analytics infrastructure, employ competent analytical personnel, and develop and apply predictive models. It is consequently operationalized as a second-order construct comprising Data Quality and Accessibility, Analytics Infrastructure, Analytical Skills and Expertise, and Predictive Modelling Capability, reflecting the view that predictive analytics value depends on the combined strength of these resources.

2.2 Data-Driven Decision-Making

Data-Driven Decision-Making is the process of making decisions in an organization based on relevant data, analytical evidence and information, and not on intuition or personal judgment. According to the conceptualization of analytical decision-making culture presented by Szukits and Móricz (2024), the use of data during the various phases of decision-making within the

organization results in an analytical culture. They also demonstrate that the top management's support for analytics and the perceived data quality are key to robust analytical cultures. Their results also show that fostering an analytical culture does not necessarily mean driving data-driven decision-making, which underscores the need for organizations to use analytical information as they make decisions. Likewise, Chaudhuri et al. (2024) associate data-driven culture to organizational capabilities and performance, which implies that the analytical information is valuable when integrated into the organizational processes. More recent studies have also stressed the need for not only the implementation of analytical technologies but also for the creation of new decision routines, organizational practices and the use of information that goes beyond traditional notions. Some of the indicators used for DDDM have been consistently measured include managers' reliance on analytical information, using data when considering alternatives, evidence-based decision making, and using analytical information in strategic and operational decisions. In this study, DDDM is the process of transforming the predictive analytics capability into organizational action. It then measures whether FMCG SMEs actually apply predictive insights in their financial, risk and operational decision-making, or just have analytics technologies.

2.3 Organizational Analytics Culture

Organizational Analytics Culture is the shared values, expectations, practices and norms within an organization that foster the use of data and analytics in decision making across the organization, both in the day-to-day and strategic sense. The environment conducive to an analytical culture is to a certain extent formed by management support for business analytics and confidence in data quality, which lead to increased data visibility in company decision-making processes (Szukits and Móricz, 2024). Data-driven organizational culture is also identified as a significant factor of organizational culture that is linked with innovation, process improvement, and business performance (Chaudhuri et al., 2024). Their findings indicate that analytics culture is a key factor for the successful conversion of technological investments into organizational capacities and results. Moreover, recent studies have highlighted that data-driven initiatives can have challenges due to data-driven tensions in organizations where there are conflicts in values, practices and approaches to data use (Bertels et al., 2024). Researchers have consequently often studied analytics culture by measuring perceptions of management support, encouragement of decision-making using analytics, employee openness to analytics, analytical learning, and the extent of data use in organization's workflow. In the current study, OAC is the organizational context in which PDAC has a positive or negative impact on performance. It reflects leadership commitment, employee acceptance, organizational support, and value placed on data and analytics as usual methods of decision-making in FMCG SMEs.

2.4 Organizational Performance Enhancement

Organizational Performance Enhancement is that which has been achieved by the effective deployment and use of the organizational resources and capabilities, leading to improvements in

organizational outcomes. Organizational performance is increasingly looked at in today's research as multidimensional rather than using only financial indicators. Vesterinen et al. (2024) see analytics capability as a tool that can help to enhance the performance of the firms by making their operations more responsive and effective around market opportunities. Similarly, Orero-Blat et al. (2025) show that analytics capabilities can be associated with enhanced organizational performance if they are put to use under the right conditions, for 183 SMEs. Chaudhuri et al. (2024) also link data-informed organizational practices with process performance and innovation and organizational value, thereby further stressing the need to look at performance beyond financial ones. The performance of organizations has thus been measured in the past in various ways, including financial results, operational efficiency, productivity, innovation, responsiveness, and other measures of effectiveness. Organizational performance enhancement is a specific term that has been defined in this study as improvement in organizational outcomes due to the use of predictive data analytics. The construct is not a measure of overall firm performance, but instead centers on three outcomes which are directly related to the objectives of the study: Financial Forecasting Accuracy, Risk Management Effectiveness, and Operational Efficiency. Financial forecasting accuracy refers to predictions of sales, revenue, cash flows and demand; risk management effectiveness is about the identification, assessment, monitoring and risk management of risks; operational efficiency is related to resource utilization, inventory, productivity and process performance. In this way, OPE offers the result by which the organizational value of PDAC can be evaluated.

2.5 Theoretical Review

2.5.1 *Dynamic Capabilities Theory*

Dynamic Capabilities Theory was developed mostly by Teece, Pisano and Shuen (1997) who claimed that in a dynamic environment, firms get competitive advantage by integrating, building and reconfiguring internal and external competencies. The theory is built on the premise that resources are not enough in themselves to ensure performance; organizations can only truly perform by continually sensing opportunities and threats, taking advantage of opportunities, and adapting (or reconfiguring) resources to meet the changing environment. The companies' ability to adjust themselves to technological and market changes is its main attribute, as opposed to considering organizational characteristics as fixed. But, the concept of DCT has been criticized for its conceptual ambiguity, especially the difference between DCT and other capabilities and the empirical measure of DC. Still, recent studies prove its continued relevance in the realm of analytics and SMEs. Dri and Su (2024) apply DCT to elucidate the role of big data analytics capabilities in the international performance of manufacturing SMEs and Orero-Blat et al. (2024) link analytics capabilities to innovation and organizational performance. Likewise, a recent study by MSME indicates that digital skills and dynamic capabilities help companies adjust to environmental changes faster and enhance their performance (Kurniawan et al., 2025). DCT is the

most appropriate study as predictive data analytics capability (PDAC) is a dynamic organizational capability, which enables the FMCG SMEs to build data, infrastructure, analytical knowledge and predictive modelling capacity to look for market conditions and reconfigure decisions. It also covers the importance of organizational analytics culture in the successful implementation of these capabilities to performance.

2.5.2 Organizational Information Processing Theory

The Organizational Information Processing Theory was mostly developed by Galbraith (1973, 1974) and suggests that the performance of an organization is dependent on the fit between the information-processing needs and the information-processing capacity of the organization. It assumes that increasing uncertainty in the environment, the complexity of the task and interdependence result in an increased amount of information that an organization has to process. A firm may react to this either by decreasing the information that it needs to process, or, more effectively in dynamic situations, by increasing its ability to process the information by means of information systems, lateral relationships, coordination mechanisms, and analysis skills. A significant advantage of OIPT is the direct explanation of how information can be a basis for organizational decision making and performance. Its disadvantage is that it can focus more on structures of information and processing capacity than on human, cultural and behavioral aspects. But recent studies have branched off into analytics research directly from OIPT. Wang et al. (2024) define the concept of big data analytics capability as an information-processing capability under uncertainty for organizations to collect, analyze and integrate information. Pang et al. (2025) also demonstrate the linkage between digital intelligence technologies and organizational performance through data analytics capability. Moreover, Jiang et al. (2025) use OIPT to show that the capability of analytics enhances firms' capability to process information related to disruption and contribute to resilience. OIPT is particularly well suited for the present study because PDAC adds to the firm's capacity to process complex and uncertain information, DDDM is the transformation of processed information into organizational decisions, and OAC is the level of capacity to integrate the capacity to process complex and uncertain information into the organizational practice. The theory offers a solid explanation for the suggested pathway from PDAC to DDDM to organizational performance, and for why the link is stronger or weaker as a result.

2.6 Empirical Review

2.6.1 Predictive Data Analytics Implementation among SMEs in the FMCG Industry

As the use of predictive data analytics continues to grow, it has revolutionized the way business information is gathered, processed and leveraged by organizations for better decision making and competitiveness. In various sectors, recent studies show that companies are shifting from reporting to predictive technologies that help them to predict future events and make more proactive management decisions. In their study, Ahmed et al. (2025) examined how AI and ML are shaping business analytics through the lens of 12 industry case studies, covering finance, healthcare, retail,

digital marketing, and supply chain management. The study revealed that AI-driven predictive analytics led to greater organizational agility, improved financial performance, better risk management, and the innovation it allowed through quick and precise decision-making. Yet, across the 14 areas, the authors noted that organizations still had hurdles to address in order to implement predictive analytics successfully, including issues with data integration, employee skills and knowledge, governance and algorithmic bias. Predictive analytics can also help businesses better understand consumer choices and make informed decisions. Duah et al. (2025a) used predictive models to examine factors affecting health insurance coverage choices in the United States, with affordability and socioeconomic factors playing an important role. Although the study focused on health insurance, it shows how predictive modelling can help businesses understand key factors and make better decisions. Riipa et al. (2025) also found similar results in their study exploring the use of data analytics to improve business decision-making and operational efficiency of 200 businesses, adopting a mixed methods design. They found that companies with a more advanced analytics competency had a better decision accuracy, profitability, operational cost and customer satisfaction than companies with less mature analytics adoption. The incorporation of predictive technologies into the functioning of organizations proved to be of vital importance, especially in the context of improving the efficiency of the supply chain and boosting revenues, which were achieved through machine learning applications. While both studies showed that predictive analytics positively affects the organization's performance, they also demonstrated that predictive analytics is not just about having the analytical software but about the organization's skill, readiness, and capability to use it effectively. This is especially true for SMEs in the United States FMCG industry, where the availability of technological infrastructure, data, employee analytical skills, and predictive modelling skills can mean either positive or negative business value from predictive analytics.

Additional research indicates that predictive analytics proficiency is more likely to yield desired results if it is backed by the right technology and analytical skills. In business-to-business financial service companies, Uddin (2025) found that companies that developed an integrated predictive analytical system did very well compared to companies that used traditional forecasting methods. The machine learning forecasting systems were the best in forecasting accuracy, and integrated business intelligence platforms lead to forecasting responsiveness, customer acquisition prediction, and operational coordination. The results suggest that predictive analytics implementation is not a technological solution but needs to be part of coordinated interactions between data systems, analytical applications and organizational processes. Similar findings are reported by Celestin, Vinayakan and Sujatha (2025) who explored predictive statistical modeling in the context of corporations in competitive markets. Their mixed-methods study showed that the financial forecasting accuracy of the advanced predictive models (Random Forest, Neural Networks, ARIMA, and Support Vector Machines) was significantly higher, with the Random Forest model performing the best in terms of prediction. The researchers also suggested that to

reap full benefits of predictive technologies from the organization, the use of cloud-based analytics, hybrid use of analytics, and constant workforce upskilling should be adopted. These findings are supported by the study carried out by Eyinade et al. (2025), which reviewed 43 empirical studies on the use of artificial intelligence in financial forecasting. They found that machine learning and deep learning always outperformed traditional statistical forecasting methods, but that there were still some concerns with transparency, data quality, regulatory compliance and interpretability. The review was not about whether predictive analytics are useful, but rather the need for explainable AI and human-AI collaboration. All of these studies indicate that the implementation of predictive analytics is a multi-dimensional organizational ability that relies on quality data, modern infrastructure, business analytic capabilities and predictive modelling. This evidence is in line with the present study, which defines Predictive Data Analytics Capability as a second order construct consisting of Data Quality and Accessibility, Analytics Infrastructure, Analytical Skills and Expertise, and Predictive Modelling Capability, and extends the previous research to SMEs in the United States FMCG industry, where empirical evidence is still relatively scarce.

However, there is also a growing body of evidence that the implementation of predictive analytics within an organization goes beyond technology and is also about organizational readiness, organizational integration and ongoing learning. Zainal and Faiz (2025) studied predictive models with machine learning techniques in large organizations and noted that the predictive accuracy improvement was not directly correlated with any benefits to the organization until predictive systems were well integrated into the organizational processes. In fact, the level of sophistication in the predictive models did not necessarily lead to more practical benefits when it came to using them, their analysis found, as legacy systems, technology environments that were not unified, and structural bottlenecks often limited the use. Similarly, Maex (2026) examined the impact of the General Data Protection Regulation (GDPR) on internal information quality and operational efficiency for U.S. companies that had operations in Europe. The regulation added some compliance regulations, but companies adapted them by improving the information quality and governance inside the company, which in turn increased efficiency of operations. The results show that data quality and governance support are key enablers to success in analytics implementation. A similar finding came from Majumder (2025) who conducted a quantitative study and identified that organizations which had accurate forecasting systems, adaptive budgeting approaches and modern planning techniques reported higher financial performance and better strategic outcomes, compared to those organizations that used less sophisticated planning practices. The findings confirm the need to incorporate sound predictive tools in organizational planning. The body of literature as a whole is consistent that the use of predictive analytics to be effective requires an interplay of good quality data, suitable technological enablers, analytical expertise, governance arrangements and organizational processes. Nevertheless, there has been a focus in most of the existing research on large organizations, financial institutions, healthcare systems, manufacturing

organizations or multinational companies. The attention to the empirical study of SMEs working in the FMCG sector in the United States is comparatively small, with the reasons for these differences being organizational resource constraints, data capability differences, and differing levels of maturity for analytics, which may impact predictive analytics implementation differently. The research aims to fill this gap by measuring the penetration and application of predictive data analytics in FMCG SMEs and understanding the most used tools and applications of predictive analytics in their operational processes.

2.6.2 Influence of Predictive Data Analytics Capability on Financial Forecasting, Risk Management, and Operational Efficiency

A robust empirical literature has established that having a capability with predictive data analytics is an important driver of increasing the accuracy of financial forecasting, improving risk management processes and increasing operational efficiencies in various organizational contexts. The research of Uddin (2025) suggests that these systems of predictive analytics can greatly enhance the accuracy of predictions in business-to-business financial service companies. The research found that companies that implemented machine learning-based forecasting systems had significantly better forecasting accuracy than companies that used traditional forecasting systems, and that they also had improvements in forecasting accuracy in customer acquisition prediction and revenue estimation stability. The results also indicated that predictive analytics increased the responsiveness to forecasting and operational coordination, indicating that there is a direct link between the capability of analytics and improvements to financial planning results. Building on this, Celestin (2025), Vinayakan and Sujatha (2025) concluded that in a competitive business landscape, the accuracy of financial forecasting can be enhanced significantly by using advanced statistical and machine learning techniques such as Random Forest and Neural Networks. The findings showed that the more complex the model, the more accurate the predictions were, further evidence that the ability to predict is more than just a technical skill, but a factor that influences strategic financial success. The results confirm those of Majumder (2025), who noted that companies with correct forecasting and budgeting systems had better financial performance measures like ROI, ROA, and operating margins. The study validated that data-driven financial planning can minimize forecasting error and make the decisions of organizations more aligned. In each such study, financial forecasting is not a stand-alone analytical process, but rather a result of the integration of predictive capabilities into organizational processes.

In addition to forecasting accuracy, the ability of predictive data analytics is also closely associated with better effective risk management. Chowdhury and Alvee (2025) offer robust empirical support in this regard from a study that takes place in the U.S. health care finance system. The results showed that predictive analytics capability can greatly help improve the effectiveness of risk management by better identifying financial anomalies like claim denials, audit exposure and fraud risks. The research revealed that a significant amount of variance in risk management

outcomes is accounted for by predictive analytics, and that the more prepared the organization is for governance, the more it is prepared to integrate data, and the more it can take action, the stronger this relationship is. Likewise, Fallahieh et al. (2025) analyzed the data analytics capability in SCs and determined that companies having a higher capacity of data analytics had a better opportunity to recognize, evaluate and reduce operational risks. They found that risk management performance partially mediates the relationship between analytics capability and organizational performance, suggesting that predictive systems can lessen the uncertainty by providing enhanced visibility and rapid responses. This data is complemented by the study conducted by Diameh et al. (2025) which showed that AI's predictive capabilities have a strong positive effect on project risk management by identifying risk early, more accurately quantifying risks and better risk mitigation. They also highlighted some issues of model interpretability and integration with current systems, indicating that the effectiveness of risk management is linked to both the analytical depth and the organizational readiness. Taken together, these studies suggest that predictive data analytics capability enhances risk management by making it more accurate, faster to respond and more traceable from a different context of operations.

Another recurring benefit of predictive data analytics capability in empirical studies is the enhanced operational efficiency, though this tends to vary depending on the degree of integration of systems into the organization and its organizational structure. Zainal and Faiz (2025) uncovered that machine learning-based predictive models could significantly improve the efficiency of business operations within large-scale companies by optimizing resource utilization, predicting demand more accurately, and minimizing delay in operational processes. The study also observed that legacy system and organizational bottlenecks can reduce the impact predictive improvements can have on operations. This was consistent with the findings reported by Riipa et al. (2025), which showed that operational efficiency gains, such as quicker reaction to market, and cost reduction in operations from the use of advanced analytics by firms was significant. Their findings indicated the benefits of predictive analysis on improving the performance of the supply chain and process optimization, particularly when incorporated into the organizational decisions process. Likewise, Ahmed et al. (2025) highlighted that AI-based predictive analytics enhances process agility, operational responsiveness, and innovation potential across various industries, but data integration difficulties and the need for employee adaptation to AI persist. Moreover, Maex (2026) offered a complimentary view by demonstrating that regulatory compliance-induced internal information quality improvements indirectly boosted operational efficiency for firms subject to GDPR. This means that operational efficiencies can be achieved through enhanced data governance and data quality rather than just predictive models. The body of literature as a whole suggests that the predictive data analytics capability enhances operational efficiency by offering improved accuracy in forecasting, optimizing resource utilization, and improving process coordination. The extent of the impact, however, can differ depending on organizational structure, data quality and degree of

integration between predictive systems and operational processes, especially for FMCG SMEs where resource limitations can influence the impact of implementation.

Predictive analytics has also shown potential in helping organizations identify cybersecurity risks. Duah et al. (2025b) examined phishing detection using a dataset of 11,055 labeled websites and applied L1-regularized logistic regression to assess structural, behavioral, and domain-related features. Their findings indicated that structural and domain features were useful in distinguishing phishing websites from legitimate ones. The study also demonstrated how interpretable predictive models can help organizations identify potential threats and support more informed risk-related decisions. Although the study focused on cybersecurity rather than FMCG operations, it provides further evidence of how predictive analytics can be used to identify risk signals and improve decision-making.

2.6.3 Data-Driven Decision-Making as Mediator and Organizational Analytics Culture as Moderator

Many empirical studies have emerged and have revealed that the value of predictive data analytics capability is not a given, but rather it is largely passed down via data-driven decision-making processes. Research has repeatedly demonstrated that performance is improved when the outputs of analysis are integrated into decision making processes, rather than being used merely to backfill the information. Sagar and Sagar (2026) explored the link between data-based decision-making and organization resilience, finding that organizations that make decisions based on structured data have quicker response times and better situational awareness, and build adaptive capacity during uncertainty. The results showed that data-driven decision-making enhances strategic, operational, and adaptive resilience by ensuring that decisions are made based on real-time data analysis and not just on intuition. More important the study also pointed out that data has little impact on outcomes without analytical skills and human judgment, so that the quality of interpretation and application of data is a key influence on the quality of the decision. In the same way, Fallahieh et al. (2025) revealed that analytics capability positively affects firm performance via risk management and supply chain performance, suggesting that decision processes serve as an intermediate variable between analytics and firm performance. According to their findings, more cohesive firms have an enhanced degree of strategic coherence and performance sustainability when they have better decision alignment between analytics insights and operational actions. Similarly, Diameh et al. (2025) found that AI-powered predictive analytics is more effective at enhancing project risk outcomes when organizations embrace proactive decision processes that enable early detection and action on risks. The study also highlighted that predictive insights need

to be integrated into decision-making processes to truly impact efficiency and cost control during a project. These studies, together, show that data-driven decision-making is not a passive effect, but an active organizational competency that translates predictive analytics into tangible performance effects, and is a key mediator in the relationship between analytics and performance.

The importance of organizational analytics culture as a moderating variable that could either positively or negatively influence the degree to which predictive analytics capability leads to outcomes has also been well known. There is evidence that even the most sophisticated analytical systems are of little use when the use of data is not ingrained in the culture, leadership and strategy of the organization. Ahmed et al. (2025) discovered that organizational agility and financial outcomes benefit greatly from AI-driven predictive analytics, though the impact varied from company to company, attributable to differing levels of organizational preparedness, leadership backing, and cultural receptivity to analytics-driven decision-making. According to their research, organizational culture influences the effectiveness of the employees' interactions with predictive systems and the use of analytical information. In a similar vein, Chowdhury and Alvee (2025) noted that governance preparedness and compliance frameworks play a key role in the successful application of predictive analytics for risk management. The study showed that while predictive analytics can achieve better results in terms of the effectiveness of risk management, it must be complemented by strong governance structures and organizations, indicating that cultural and structural factors can moderate the outcomes of analytics efforts. This was complemented by a finding from Zainal and Faiz (2025) that the usefulness of machine learning systems was limited by legacy systems and people's resistance to change if they were not embedded in enabling organizational contexts. The findings as a whole confirm the importance of the organizational analytics culture in the success of predictive analytics efforts, characterized as openness to data use, leadership commitment and institutional support. If there's no such culture, even sophisticated analytics infrastructure could not deliver the expected performance gains.

Empirical findings continue to support the notion that organizational analytics culture and decision-making influence the successful implementation of predictive analytics capability throughout various industries. Riipa et al. (2025) discovered that businesses with higher analytics maturity and stronger data use cultures had better decision accuracy, are more responsive to the market, and were more efficient in their operations. The study also highlighted the importance of leadership efforts in improving the chance of predictive insights being put into the day-to-day decision-making process. In another contribution, Majumder (2025) demonstrated that companies that embraced a flexible budgeting and forecasting system saw improved financial results when their decision-making processes were participatory and data-driven, highlighting the significant role an organization's norms play in determining their performance outcomes. Likewise, Celestin, Vinayakan and Sujatha (2025) suggested training the workforce to upskill and hybrid analytical methods as key factors in achieving maximum effectiveness of analytics model, thereby indirectly highlighting the significance of organizational culture of learning in influencing analytics

outcomes. Moreover, Eyinade et al. (2025) cited the need for explainable AI and human-in-the-loop AI systems, stating that the interpretability of AI analytical tools and trust in them is vital for decision-making adoption. This underlines that organizational culture impacts not only on usage, but also on trust, acceptance and reliance on predictive systems. Together, these studies indicate that the role of predictive analytics capability in determining organizational performance is the most direct and predictive, and that organizational analytics culture exacerbates or mitigates that relationship based on the extent of leadership support, employee competency, governance, and openness to analytics-driven practices. These dynamics are critical for SMEs in the FMCG industry, where resource constraints and different degrees of digital maturity can increase the impact of organizational culture on the impact of predictive analytics.

2.7 Study Hypothesis and Conceptual Model

The existing evidence, as reviewed, generally indicates that predictive data analytics capability can enhance organizational outcomes when firms possess the necessary data, technological infrastructure, analytical expertise, and modelling capabilities. These capabilities are particularly important for improving the accuracy and reliability of financial forecasting. Therefore, the study proposes that the core dimensions of predictive data analytics capability will positively influence financial forecasting accuracy as follows:

- H1: Data Quality and Accessibility has a significant positive effect on Financial Forecasting Accuracy among SMEs in the FMCG industry in the United States.
- H2: Analytics Infrastructure has a significant positive effect on Financial Forecasting Accuracy among SMEs in the FMCG industry in the United States.
- H3: Analytical Skills and Expertise has a significant positive effect on Financial Forecasting Accuracy among SMEs in the FMCG industry in the United States.
- H4: Predictive Modelling Capability has a significant positive effect on Financial Forecasting Accuracy among SMEs in the FMCG industry in the United States.

Similarly, effective risk management depends on the ability of firms to access reliable information, apply appropriate analytical technologies, possess relevant analytical expertise, and use predictive models to identify potential risks in advance. The study therefore expects the dimensions of predictive data analytics capability to positively influence risk management effectiveness, as presented in the following hypotheses:

- H5: Data Quality and Accessibility have a significant positive effect on Risk Management Effectiveness among SMEs in the FMCG industry in the United States.
- H6: Analytics Infrastructure has a significant positive effect on Risk Management Effectiveness among SMEs in the FMCG industry in the United States.

- H7: Analytical Skills and Expertise have a significant positive effect on Risk Management Effectiveness among SMEs in the FMCG industry in the United States.
- H8: Predictive Modelling Capability has a significant positive effect on Risk Management Effectiveness among SMEs in the FMCG industry in the United States.

Again, predictive data analytics can also support operational efficiency by enabling firms to improve resource allocation, streamline processes, respond more quickly to changing conditions, and reduce avoidable operational costs. On this basis, the study hypothesizes that key dimensions of predictive data analytics capability will have positive effects on operational efficiency:

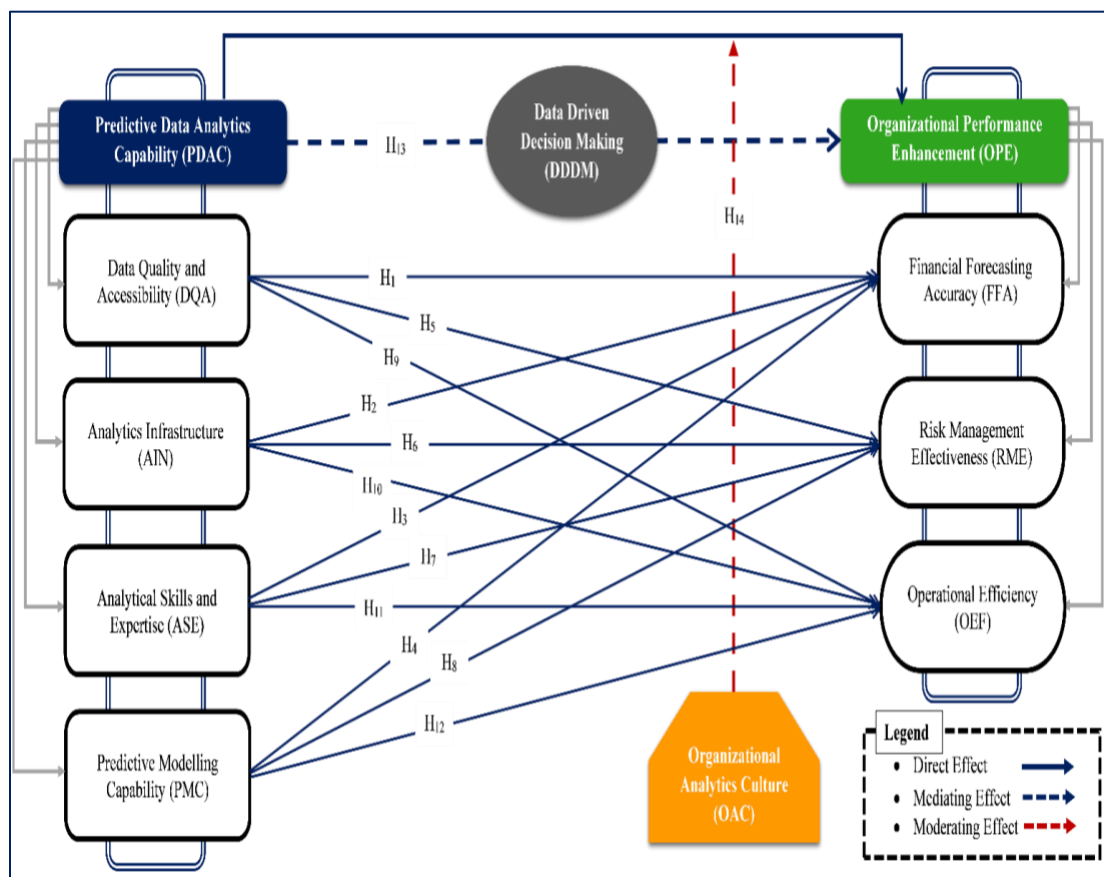
- H9: Data Quality and Accessibility have a significant positive effect on Operational Efficiency among SMEs in the FMCG industry in the United States.
- H10: Analytics Infrastructure has a significant positive effect on Operational Efficiency among SMEs in the FMCG industry in the United States.
- H11: Analytical Skills and Expertise have a significant positive effect on Operational Efficiency among SMEs in the FMCG industry in the United States.
- H12: Predictive Modelling Capability has a significant positive effect on Operational Efficiency among SMEs in the FMCG industry in the United States.

The benefits of predictive data analytics may depend not only on the capability to generate and analyse data but also on how analytical information is incorporated into organizational decisions and the organizational environment in which analytics is implemented. Data-driven decision-making is expected to provide a mechanism through which predictive data analytics capability contributes to organizational performance enhancement, while an organizational analytics culture that supports data-based decisions and analytical practices may strengthen this relationship. Based on these relationships, the study proposes the following hypotheses:

- H13: Data-Driven Decision-Making mediates the relationship between Predictive Data Analytics Capability and Organizational Performance Enhancement among SMEs in the FMCG industry in the United States.
- H14: Organizational Analytics Culture positively moderates the relationship between Predictive Data Analytics Capability and Organizational Performance Enhancement among SMEs in the FMCG industry in the United States.

The conceptual model of the study is shown in Figure 1, which presents a graphical overview of the study hypothesis.

Figure 1. Conceptual Model of the Study



3. Materials and Methods

3.1 Industry Focus Justification

The Fast-Moving Consumer Goods industry is one of the most dynamic sectors of the United States economy because of its high sales volumes, high inventory turnover, long supply chain and intense market competition (Monyei et al., 2025). This area includes food products, beverages, household products, personal care items and other common items purchased by consumers. The industry has seen a rise in the demand for data-driven business strategies, owing to the constant changes in customer preferences, fluctuations in demand, inflationary pressures, and uncertainties in the supply chain (Safronchuk et al., 2025). New advances have also prompted a heightened rivalry among the FMCG companies, with retailers and manufacturers turning to forecasting technologies, customer analytics and digital platforms to gain a better edge in the market and in their operations as they seek to be more sensitive to market conditions (Financial Times, 2025). SMEs are a major part of the business landscape in the USA and have a significant role in the production, distribution, retailing and wholesale activities of FMCGs. The U.S. Small Business Administration (SBA) estimates that there were about 34.75 million small businesses in the United States in 2024, with 45.9% of the nation's private sector workforce employed by them (U.S. Small Business Administration, Office of Advocacy, 2024). In addition, SMEs account for approximately 43.5% of the national Gross Domestic Product (GDP) and SMEs are playing an important role in economic growth and job creation (Office of Advocacy, 2024). With the increased trend of predictive data analytics tools, these companies have grown with potential to enhance the quality of decisions and effectiveness of operations. Despite this, adoption rates and organisational capacity to implement predictive data analytics are not uniform, so the industry provides a suitable industry setting to explore the association between predictive data analytics capability with enhanced organisational outcomes.

3.2 Research Design

This study adopted a quantitative research approach using a cross-sectional survey design. The quantitative approach was appropriate as it aims to explore the relationship between measurable constructs and test the hypothesised relationships between the predictive data analytics capability, data driven decision making, organisational analytics culture, and organisational performance enhancement (Lim, 2025). The use of quantitative methods also allows for the use of more complex statistical methodology like the Structural Equation Modelling (SEM) and the Fuzzy Set Qualitative Comparative Analysis (fsQCA), which are appropriate tools for studying net effects and configurational relationships between variables. The cross-sectional design guided the collection of data from the respondents at one-time. This design is commonly employed in business and management research for studying relationships between variables and describing existing conditions without changing the conditions of the study environment (Maier et al., 2023). Primary data was collected from respondents using a structured survey instrument, which ensured that these

data represented the current organizational practices and experiences of implementing predictive analytics.

3.3 Study Target Population

The study's target sample included decision makers and professionals who are directly involved in data related planning, analytics implementation and strategic decision making as well as operational management in FMCG SMEs in the United States. These participants were deemed suitable as they have knowledge of analytics adoption, capabilities of the organization and performance outcomes. These specific groups of SMEs Owners, chief executive officers (CEOs), managing directors, finance managers, financial controllers, operations managers, supply chain managers, business intelligence managers, data analytics managers, it managers and strategic planning managers were the target participants. In the context of this study, the accessible population comprised FMCG SMEs operating in wholesale trade, food distribution, consumer goods distribution and related FMCG activities. According to available industry data, the nondurable goods merchant wholesale trade industry (including grocery and related products merchant wholesale trade and other FMCG related industries) consisted of about 183,341 establishments in 2025 (U.S. Bureau of Labor Statistics [BLS], 2026). The majority of these establishments are SMEs and this was used as the population for sample size calculation.

3.4 Sample Size Computation

The sample size was determined using the formula proposed by Yamane (1967):

$$n = \frac{N}{1 + N(e^2)} \dots \dots \dots equ (1)$$

Where; n = Sample size, N = Population size, e = Level of precision or margin of error (0.05). Using the estimated population of 183,341 FMCG related SME establishments, the sample size is computed as follows:

$$\begin{aligned} n &= \frac{183,341}{1 + 183,341 (0.05)^2} \\ n &= \frac{183,341}{1 + 183,341 (0.0025)} \\ n &= \frac{183,341}{459.3525} \\ n &= 399.13 \approx 399 \end{aligned}$$

Therefore, the minimum sample size required for the study was 399 respondents. Since one qualified respondent was selected from each participating SME, the study also required a minimum of 399 respondents. To minimize the effects of non-response, incomplete questionnaires, and

unusable responses, approximately 450 respondents from 450 FMCG SMEs were targeted for data collection.

3.5 Sampling Techniques

A combination of purposive sampling and simple random sampling techniques was employed. Purposive sampling method was employed to identify FMCG SMEs and select the respondents who hold managerial and decision-making positions relevant to the study objectives and which met the target population criteria for the study. This helped to ensure that only people who were knowledgeable about analytics practices and organizational processes took part in the study. Later, simple random sampling method was employed for selection of respondents from the eligible pool of participants. The random selection process was conducted using the Random.Org True Random Number Generator, an online randomization tool widely used in academic research to eliminate selection bias and provide each eligible participant with an equal chance of selection (Mannalath et al., 2023). Purposive and simple random sampling techniques were used to make the respondents' responses relevant and yet ensure the objective selection of the respondents (Obilor, 2023).

3.6 Study Instrument

A semi structured questionnaire that is specially designed for this study was used to collect data. The questionnaire comprised three parts corresponding to the objectives of the study and its conceptual framework. The socio demographic characteristics of respondents such as gender, age, educational qualification, job position, years of work experience, firm size and years of organizational operation were collected under section 'A'. In Section 'B', the level, effectiveness and the most common uses of predictive data analytics in FMCG SMEs were explored. The variables studied were the level of analytics adoption, how often they use analytics, how long they use analytics for, where they use analytics, what type of analytics tools they use, and their perception of the effectiveness of being able to use analytics. Section 'C' quantified the study constructs which consisted of Predictive data analytics capability, data quality and accessibility, analytics infrastructure, analytical skills and expertise, and predictive modelling capability, data driven decision making, organizational analytics culture, organizational performance enhancement, financial forecasting accuracy, risk management effectiveness and operational efficiency. The questionnaire was designed based on concepts and dimensions that emerged in previous empirical studies, and tailored to the context of FMCG SMEs in the United States. Appendix 'A' presents a copy of the complete questionnaire.

3.7 Data Collection Procedure

Data collection took place across 12 weeks from March to May 2026. Prior to the commencement of the main survey, permission was obtained from participating organizations and relevant gatekeepers. Initial contact was mainly through telephone calls and face-to-face visits with selected

organisations. These preliminary interactions were for the purpose of explaining the study, ensuring participants' confidentiality, and asking for their participation in the survey. Prior to the main data collection exercise, a pretest of the questionnaire was conducted with 30 respondents from the FMCG SMEs having characteristics similar to those of the study target population but were not included in the final survey exercise. The pretesting exercise took place in selected SMEs located in Texas and Illinois. The feedback that was received from the participants showed that some of the technical terms in the context of predictive analytics were not consistently understood by some of them. Some also indicated that they would like to see some of the statements made more simply and see the questionnaire layout improved to make it easier to read and fill out. From these observations, ambiguous expressions were altered and a few questions were reworded to use simpler business language, instructions were clarified and minor formatting changes were made prior to finalizing the instrument for the main study.

Face-to-face administration method was used in the main survey. In face-to-face approach, the appointments were arranged with the involved organizations and the questionnaires were distributed to the respondents in the working hours. This allowed to give more detailed explanations on the purpose of the study and to answer any concerns raised by the respondents prior to the completion of the questionnaire. The participants were generally interested in the study, as many believed predictive analytics was an emerging field of great strategic interest in their organizations. Completed questionnaires were rated on a regular basis for missing responses, incomplete questionnaires and inconsistencies during the data collection period. If significant portions of questionnaires were found to be unfilled, the respondents were politely contacted and asked to fill in the missing areas if they wished.

Every questionnaire completed was given an identification code to help identify and organise questionnaires for subsequent data processing. To ensure the anonymity and confidentiality of the data, personal identifiers were removed during data preparation. After data cleaning, coding and screening, the final data was exported in the IBM SPSS Statistics software, SmartPLS software, fsQCA software, R software for further analysis. This process ensured accuracy, consistency and adherence to accepted research ethics and data protection.

3.8 Study Variable and Measurement Construct

This study uses a multidimensional model which has independent variables, mediating variables, moderating variables, and dependent variables (Table 1). Predictive Data Analytics Capability (PDAC) is the second order independent construct, which is measured by four first order dimensions: Data Quality and Accessibility (DQA), Analytics Infrastructure (AIN), Analytical Skills and Expertise (ASE), Predictive Modelling Capability (PMC). The second order dependent construct is Organizational Performance Enhancement (OPE), which is measured by Financial Forecasting Accuracy (FFA), Risk Management Effectiveness (RME) and Operational Efficiency

(OEF). Data Driven Decision Making (DDDM) is the mediating variable, and Organizational Analytics Culture (OAC) is the moderating variable.

All latent variables were assessed by reflective measures, which are also adapted from existing empirical literature and tailored to the context of FMCG SMEs in the United States. Construct items were answered on a five-point Likert scale from strongly disagree (1) to strongly agree (5). Reflective measurement scales have been suggested by Lambert et al. (2023) for use when indicators are manifestations of a construct and are expected to covary.

Table 1. Study Variables and Measurement Constructs

Variable Type	Construct	Code	Number of Items
Independent Variable (Second Order)	Predictive Data Analytics Capability	PDAC	5
First Order Dimension	Data Quality and Accessibility	DQA	5
First Order Dimension	Analytics Infrastructure	AIN	5
First Order Dimension	Analytical Skills and Expertise	ASE	5
First Order Dimension	Predictive Modelling Capability	PMC	5
Mediating Variable	Data Driven Decision Making	DDDM	5
Moderating Variable	Organizational Analytics Culture	OAC	5
Dependent Variable (Second Order)	Organizational Performance Enhancement	OPE	5
First Order Dimension	Financial Forecasting Accuracy	FFA	5
First Order Dimension	Risk Management Effectiveness	RME	5
First Order Dimension	Operational Efficiency	OEF	5

3.9 Reliability and Validity Assessment

The structural model evaluation was preceded by reliability and validity assessment. Cronbach's Alpha (α), Composite Reliability (CR) and rho_A were employed to check the internal consistency reliability. For acceptable reliability, Hair et al. (2021) is followed to use values equal or greater to 0.70. Additionally, convergent validity was evaluated using factor loadings and Average Variance Extracted (AVE). The factor loadings were expected to be higher than 0.70 and the AVE values were expected to be greater than 0.50, which means that the construct accounts for over 50% of the variance of the indicators (Fornell & Larcker, 1981). Furthermore, the discriminant validity was checked by the Fornell Larcker Criterion and the Heterotrait Monotrait Ratio (HTMT). The discriminant validity among constructs was adequate (Hair et al., 2021) when the values of HTMT were less than 0.85. See Table 2.

Table 2. Reliability and Validity Assessment Criteria

Assessment	Measure	Recommended Threshold
Internal Consistency Reliability	Cronbach's Alpha (α)	≥ 0.70
Internal Consistency Reliability	Composite Reliability (CR)	≥ 0.70
Internal Consistency Reliability	rho_A	≥ 0.70
Indicator Reliability	Outer Loading	≥ 0.70
Convergent Validity	Average Variance Extracted (AVE)	≥ 0.50
Discriminant Validity	Fornell Larcker Criterion	Square root of AVE > correlations
Discriminant Validity	HTMT Ratio	< 0.85

Assessment	Measure	Recommended Threshold
Multicollinearity	Variance Inflation Factor (VIF)	< 5.00

3.10 Data Analysis Methods

The analysis of data was done in three successive steps, depending on the objectives of the study. The statistical analysis was carried out using IBM SPSS Statistics, SmartPLS and fsQCA software. The use of these analytical tools was deemed to be suitable, as the study aimed to explore descriptive patterns, causal relationships, mediation and moderation effects, and multiple causal configurations related to organizational outcomes. Magno et al. (2024) pointed out that Partial Least Squares Structural Equation Modelling (PLS-SEM) is well suited to predictive and exploratory studies of higher order constructs and Geremew et al. (2024) noted that fsQCA complements the traditional statistical methods by highlighting alternative combinations of conditions that yield the same outcomes.

3.10.1 Descriptive Statistical Analysis

Descriptive statistical techniques were used to accomplish the first objective. The categorical responses of analytics adoption levels, frequency of use, duration of analytics use, application areas and analytics tools were summarized using frequency distributions and percentages. To evaluate respondents' perceptions of the effectiveness of implementing predictive analytics, mean scores and standard deviations were used. Multiple response analysis was used to identify the most commonly used predictive analytics applications and tools used by SMEs. Further, cross tabulation analysis was adopted to evaluate the adoption pattern by organizational characteristics like years in operation and firm size. In particular, the descriptive analysis explored the extent of the use of predictive analytics, the frequency of their use, how long they have used analytics, the main areas of use, the type of tools used, and how effective they have found the use of analytics to be for SMEs in the FMCG sector in the United States.

3.10.2 Partial Least Squares Structural Equation Modelling (PLS-SEM)

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyze the second and third research objectives. The use of PLS-SEM is appropriate because it features higher order constructs, mediation effects, moderation effects, and prediction-oriented objectives. PLS-SEM is effective in complex models and can be applied to exploratory and predictive research, as stated by Hair et al. (2021). The direct effects structural model of the study variables of the influence of the predictive data analytics capability dimensions on financial forecasting accuracy, risk management effectiveness and operational efficiency is represented in the study variable codes in the following manner:

$$FFA = \beta_0 + \beta_1 DQA + \beta_2 AIN + \beta_3 ASE + \beta_3 PMC + \varepsilon \dots \dots \dots equ (1)$$

$$RME = \beta_0 + \beta_1 DQA + \beta_2 AIN + \beta_3 ASE + \beta_3 PMC + \varepsilon \dots \dots \dots equ (2)$$

$$OEF = \beta_0 + \beta_1 DQA + \beta_2 AIN + \beta_3 ASE + \beta_3 PMC + \varepsilon \dots \dots \dots equ (3)$$

Where ε = Error term. The mediation effect of Data Driven Decision Making was estimated using the indirect effect analysis, and modeled as expressed below:

$$OPE = \beta_0 + a' PDAC + \beta_1 DDDM + \varepsilon \dots \dots \dots equ (4)$$

Bootstrapping with 5,000 resamples was employed to determine the significance of indirect effects. On the other hand, moderation analysis was examined through an interaction term:

$$OPE = \beta_0 + \beta_1 PDAC + \beta_2 OAC + \beta_3 (PDAC \times OAC) + \varepsilon \dots \dots \dots equ (5)$$

A statistically significant interaction coefficient (β_3) will indicate the presence of a moderating effect.

3.10.3 Fuzzy Set Qualitative Comparative Analysis (fsQCA)

Following the PLS-SEM analysis, fsQCA was employed as a complementary analytical technique. Unlike regression-based methods that focus on net effects, fsQCA identifies multiple combinations of conditions that can lead to the same outcome, an idea referred to as equifinality (Andrade-Valbuena & Dos Santos, 2026). The analysis investigated configurations of $f(DQA, AIN, ASE, PMC)$ that lead to high levels of FFA, RME, OEF . Raw data was first calibrated into fuzzy set membership scores ranging from 0 to 1. Calibration thresholds followed the direct calibration procedure proposed by Ragin (2008), using full membership (0.95), crossover point (0.50), and full non membership (0.05). Consistency was calculated as:

$$Consistency(X \leq Y) = \frac{\sum \min(X_i, Y_i)}{\sum X_i}$$

Coverage was estimated as:

$$Coverage(X \leq Y) = \frac{\sum \min(X_i, Y_i)}{\sum Y_i}$$

Where X represents causal conditions and configurations, Y represents the outcome condition. Consistency values of 0.75 and above were considered acceptable for identifying sufficient configurations. The resulting solutions revealed alternative pathways through which predictive analytics related capabilities, decision processes, and organizational conditions combined to produce favorable organizational outcomes.

4. Results

4.1 Sociodemographic and Organizational Profile of Respondents

The number of respondents in the study were 400 out of which 61.3% were males and 38.8% were females. The largest age group was 35 – 44 years (34.5%), followed by 25 – 34 years (26.8%) and 45 – 54 years (20.8%). The sample was well-educated, as 43.5% of them had bachelor's degrees and 32.5% had PhD or higher degrees. The respondents held a variety of managerial roles; Managing Directors (16.3 %), Supply Chain Managers (14.2 %), and IT/Data Analytics Managers (14.2 %), covering a wide spectrum of functional areas including strategic, financial, operational, supply-chain and analytics.

Finally, the participants reported different organizational experience as illustrated in Table 3. Twenty-seven (27.0%) had 1 - 3 years' experience and 23.5% each had 4 - 6 and 7 - 10 years' experience. As to firm size, 35.3% of firms had 100-249 employees, followed by 24.3% that had 50-99 employees. Firm age was similarly diverse, with 27.3% operating for 5 – 10 years, 23.3% for 11 – 15 years, and 19.0% for 16 – 20 years.

The results also show significant implementation of predictive data analytics. 37.8% said they were advanced and 15.8% said they were fully integrated in operations; 27.3% said they were moderately advanced. 2.0% had not implemented predictive analytics. Use was also quite common, with 28.7% using analytics on a monthly basis, 28.5% on a weekly basis, and 22.5% daily. In terms of length of time, 34.0% used predictive analytics for 2 to 5 years and 25.3% for over five years. Finally, the sample is largely comprised of managerial respondents and organizations that reported some level of exposure to predictive analytics, creating an appropriate context to discuss analytics capability and organizational performance.

Table 3. Socio-Demographic and Organizational Characteristics of Respondents (N = 400)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	245	61.3
	Female	155	38.8
Age	Below 25 years	22	5.5
	25–34 years	107	26.8
	35–44 years	138	34.5

Characteristic	Category	Frequency (n)	Percentage (%)
Highest Level of Education	45–54 years	83	20.8
	55 years and above	50	12.5
	High School Diploma	20	5.0
	Associate Degree	40	10.0
	Bachelor's Degree	174	43.5
	PhD or equivalent	130	32.5
	Doctorate Degree	27	6.8
	Other	9	2.3
Current Position	Owner/Founder	45	11.3
	Chief Executive Officer	39	9.8
	Managing Director	65	16.3
	Finance Manager	49	12.3
	Operations Manager	40	10.0
	Supply Chain Manager	57	14.2
	IT/Data Analytics Manager	57	14.2
	Business Intelligence Manager	48	12.0
Years Worked in Organization	Less than 1 year	30	7.5

Characteristic	Category	Frequency (n)	Percentage (%)
Number of Employees	1–3 years	108	27.0
	4–6 years	94	23.5
	7–10 years	94	23.5
	More than 10 years	74	18.5
	Less than 50	65	16.3
	50–99	97	24.3
	100–249	141	35.3
	250–499	66	16.5
	500 and above	31	7.8
	Less than 5 years	54	13.5
Years Firm Has Been in Operation	5–10 years	109	27.3
	11–15 years	93	23.3
	16–20 years	76	19.0
	More than 20 years	68	17.0
	Not adopted	8	2.0
Level of Predictive Data Analytics Adoption	Initial adoption	18	4.5
	Basic adoption	51	12.8

Characteristic	Category	Frequency (n)	Percentage (%)
Frequency of Predictive Analytics Use	Moderate adoption	109	27.3
	Advanced adoption	151	37.8
	Fully integrated across operations	63	15.8
	Never	8	2.0
	Rarely	25	6.3
	Occasionally	48	12.0
	Monthly	115	28.7
	Weekly	114	28.5
	Daily	90	22.5
Duration of Predictive Analytics Usage	Less than 6 months	32	8.0
	6 months–1 year	43	10.8
	1–2 years	88	22.0
	2–5 years	136	34.0
	More than 5 years	101	25.3

4.2 Extent of Effectiveness and Predominant Applications of Predictive Data Analytics among SMEs in the FMCG industry in the United States

4.2.1 Predominant applications of predictive data analytics among SMEs

The first part of the first research objective seeks to identify the predominant applications of predictive data analytics among SMEs and examine the pattern of its use across different levels of adoption, firm size and firm age. The analysis also takes into account the frequency of the use of predictive analytics to specific business functions, the tools for supporting these applications and the spread of applications between SME attributes. Predictive data analytics is being used to support all 10 business functions analysed (see Table 4). Product performance analysis (68.8%, $n = 275$) was the most common application, followed by financial planning and budgeting (67.0%, $n = 268$), demand forecasting (66.8%, $n = 267$) and inventory management (66.3%, $n = 265$). Planning marketing campaigns was reported by 65.8% of respondents and customer analytics reported at 64.5%. The most highly reported were sales forecasting (64.0%), risk assessment (63.7%) and pricing decisions (63.7%) and supply chain management (60.8%). The difference between the highest and lowest rates of reporting usage of predictive analytics indicates a relatively broad distribution among business functions, not just one particular function. Product-related, financial, forecasting and inventory activities are still the most prominent uses, however.

Table 4. Predominant Applications of Predictive Data Analytics among SMEs

Application of predictive analytics	Frequency (N)	Percent of cases (%)
Product performance analysis	275	68.8
Financial planning and budgeting	268	67.0
Demand forecasting	267	66.8
Inventory management	265	66.3
Marketing campaign planning	263	65.8
Customer analytics	258	64.5
Sales forecasting	256	64.0
Risk assessment	256	64.0
Pricing decisions	255	63.7
Supply chain management	243	60.8

Applications are complemented by the pattern of technology use. The most common predictive analytics tool among SMEs was Microsoft Excel Forecasting Tools with 82.7% of respondents reporting use, followed by Power BI (74.2%) and Tableau (55.1%). Forty-nine percent were using Python, 35.3% IBM SPSS and 29.1% R. The figures for machine learning platforms (29.1%), Microsoft Azure AI (24.6%), AWS Analytics (23.8%), Google Cloud Analytics (22.3%), custom-built analytics systems (18.5%) SAP Analytics (16.8%), Oracle Analytics (15.8%) and even SAS Analytics (12.5%) were considerably lower. This trend indicates that the adoption of predictive analytics at SMEs is mostly driven by the use of relatively low-tech, common analytical tools like Excel and Power BI, rather than enterprise or custom-developed tools (See Table 5). The result is in line with the wide variety of use cases found: SMEs seem to be implementing predictive capabilities in ways that can be supported by a wider range of tools and without the need for dedicated infrastructure.

Table 5. Predictive Analytics Tools Used by SMEs

Predictive analytics tool	Frequency (N)	Percent of cases (%)
Microsoft Excel Forecasting Tools	330	82.7
Power BI	296	74.2
Tableau	220	55.1
Python	198	49.6
IBM SPSS	141	35.3
R	116	29.1
Machine Learning Platforms	116	29.1
Microsoft Azure AI	98	24.6
AWS Analytics	95	23.8
Google Cloud Analytics	89	22.3
Custom-Built Analytics Systems	74	18.5

Predictive analytics tool	Frequency (N)	Percent of cases (%)
SAP Analytics	67	16.8
Oracle Analytics	63	15.8
SAS Analytics	50	12.5
Total	1,953	489.5

The cross tabulation of application areas and adoption level also highlights that reported applications are not limited to the early adopters of analytics. The highest number of SMEs was observed in the advanced market in all application areas. For instance, 105 SMEs that reported product performance analysis, 102 customer analytics, 102 financial planning and budgeting, 101 demand forecasting and 100 sales forecasting were considered to be advanced adopters. Similarly, the adoption of advanced technologies was strong for inventory management (97), risk assessment (97), pricing decisions (94), marketing campaign planning (92), and supply chain management (89). The next largest group were for moderate adoption across most application areas, and fully integrated adoption ranged from 36 to 45 across the application areas. In contrast, the number of SMEs in the initial adoption and not adopted categories were relatively low in all reports of these applications. The distribution suggests that SMEs with more advanced adoption of predictive analytics in the functions identified are more likely to have gone beyond using it for experiments and simple implementation and have become more committed to it. Another descriptive dimension that can be added to this pattern is firm size. SMEs (100 to 249 employees) often made up the bulk of the firms in an advanced adoption category across the application areas. This was especially true of inventory management, financial planning and budgeting, product performance analysis, risk assessment, demand forecasting, customer analytics and sales forecasting; all of which had 40, 43, 43, 41, 36, 37, and 36 percent respectively of all advanced adopters in this size category. Firms with 50 - 99 employees also had a significant proportion of users for a number of applications, and the smallest numbers of users were found in the 500 plus user base for all applications. This distribution should, however, be taken in context with the sample composition rather than as proof of the association between the adoption of predictive analytics and firm size alone. Descriptively, the results suggest that medium-sized SMEs (especially those with 100 - 249 employees) make up a significant proportion of advanced users in the major application areas. When the firm's age is considered, there is a broadly similar pattern, but with some variation between applications. SMEs with 5 - 10 years operating experience often made up a significant percentage of the advanced users, at 26.0% for sales forecasting, 25.7% for demand forecasting,

22.7% for inventory management, 28.4% for customer analytics, 23.9% for marketing campaign planning, 25.5% for financial planning and budgeting, and 27.6% for product performance analysis. Important were also companies with an operating history of 11-15 years, especially in product-related applications, pricing and supply chain and financial applications. Older companies (20 years or more) tended to be smaller but still a significant percentage of advanced users. The descriptive distributions indicate that there is a good level of representation across the different levels of organizational maturity, especially amongst the SMEs with 5 to 15 years in the market.

The pattern is not limited to a specific application either, as evidenced by the firm-size and firm-age cross-tabulations. For instance, the top advanced-adoption concentrations for product performance analysis, as ranked by application overall, are in companies with 100 - 249 employees and companies that have been in operation for 5 - 10 years. Similar patterns are seen for other areas such as customer analytics and financial planning and budgeting. Demand forecasting and inventory management also present significant numbers of 100 - 249 employee firms, and supply chain management a more spread-out pattern among firm-age categories. The differences suggest that while predictive analytics is used widely throughout SME business functions, its use varies a little by application within the organization. The results show that overall SMEs' predictive data analytics is wide-spread in terms of the breadth of functions, relatively high rates of application across all ten business areas, use of available data analytics technologies to build predictive models, and a large number of advanced adopters. Product performance analysis is by far the most common application but it's only a small lead over other applications, and this indicates that SMEs are adopting predictive analytics as a multi-purpose capability rather than as a tool to pursue a single dominant application. This is a further sign that this function is predominantly realized in mainstream analytical tools, such as Excel and Power BI. This trend is confirmed by the cross tabulations, which indicate that the applications are especially concentrated in advanced adopters and descriptively in firms with 100-249 employees and those that have been in operation for 5-15 years. In conclusion, these findings indicate that predictive analytics is going beyond just forecasting and being integrated into product, financial, operational, marketing, customer, and risk-related decision-making within SMEs.

4.2.2 Effectiveness of Predictive Analytics Implementation

The second part of Objective 1 aims to evaluate the effectiveness of the implementation of predictive analytics in the SMEs for the enhancement of the organization's decision-making, operational processes and business performance. The descriptive statistics for the ten indicators measuring implementation effectiveness are shown in Table 6. The results demonstrate that the mean scores across all indicators are consistently high, ranging from 4.00 to 4.05, which suggests a fairly favorable evaluation of the implementation of predictive analytics among the SMEs surveyed. Enhanced responses to market changes and enhanced quality of organizational decisions were the best rated responses with a mean of 4.05. This was shortly followed by the accuracy of

business forecasts ($M = 4.04$). The findings indicate that the most significant perceived benefits of predictive analytics are specifically those of being able to quickly adapt to key market changes, enhance the quality of decisions and increase forecasting accuracy, which are most relevant to SMEs. Reducing operational uncertainties ($M = 4.03$), improving operational planning ($M = 4.03$) and anticipating future business trends ($M = 4.03$) were other positive assessments which were recorded. The findings show that predictive analytics is not just seen as a decision support tool, but also as an asset to enhance forward-looking and operational planning. The economic and organization benefits of implementation was also rated positively. The advantages of predictive analytics over costs ($M = 4.02$) were also identified. Likewise, predictive analytics was seen to provide better coordination within business functions ($M = 4.01$), and to have led to measurable benefits after implementation ($M = 4.01$). The lowest rated indicator but still very positive was the contribution of predictive analytics to overall business performance ($M = 4.00$).

Table 6. Effectiveness of Predictive Analytics Implementation among SMEs

Effectiveness indicator	Mean	Std. Deviation
Improved response to changing market conditions	4.05	0.790
Improved quality of organizational decisions	4.05	0.825
Improved accuracy of business forecasts	4.04	0.826
Reduced operational uncertainties	4.03	0.799
Improved operational planning	4.03	0.843
Improved ability to anticipate future business trends	4.03	0.859
Benefits outweigh the costs involved	4.02	0.831
Enhanced coordination across business functions	4.01	0.884
Achieved measurable improvements from implementation	4.01	0.861
Contributed positively to overall business performance	4.00	0.863

Standard deviations are between 0.790 and 0.884, which means that there was relatively little variation around the mean responses. The greatest difference was seen in response to changing market conditions ($SD = 0.790$) and the smallest difference was in enhanced coordination across

business functions ($SD = 0.884$). This relatively small spread indicates that generally, the participating SMEs had a fairly consistent view of the effectiveness of predictive analytics. In short, the results show that predictive analytics implementation is seen as very effective in several aspects of SME performance. The mean scores are highest for market responsiveness, decision quality and forecasting accuracy, whereas its contribution to broader business performance receives the lowest mean score. Most importantly, the average ratings for all nine indicators indicate that, not only is there a clear perception of the effectiveness of predictive analytics in individual analytical tasks, there is also a strong perception of the effectiveness of predictive analytics at the strategic level, in supporting operational planning and reducing uncertainty, and in supporting inter-functional coordination and measurable organizational benefits.

4.3 Structural Equation Modelling of Predictive Data Analytics Capability and Organizational Performance Enhancement

4.3.1 Assessment of the Structural Model

4.3.1.1 Confirmatory Factor Analysis

Before testing the hypothesized relationships, the suitability of the measurement model was assessed through confirmatory factor analysis (CFA). The analysis was conducted to evaluate the adequacy of the measurement items, determine the underlying factor structure of the constructs, and establish the appropriateness of the dataset for subsequent PLS-SEM analysis. Principal Component Analysis (PCA) with varimax rotation was initially employed, while a minimum factor loading threshold of 0.70 was adopted for retaining measurement items. The initial Principal Component Analysis (PCA) extracted 11 factors with eigenvalues greater than 1.0, which corresponded to the eleven theoretical constructs specified in the conceptual framework. The eleven-factor solution explained a cumulative variance of 81.043%, substantially exceeding the commonly accepted minimum threshold of 50%. As shown in Table 7, the first factor accounted for 26.956% of the total variance, while the remaining ten factors contributed additional explanatory power, supporting the multidimensional structure of the measurement model.

Table 7. Total Variance Explained in Data

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% Of Variance	Cumulative %	Total	% Of Variance	Cumulative %	Total	% Of Variance	Cumulative %
1	14.826	26.956	26.956	14.826	26.956	26.956	4.126	7.503	7.503

2	3.639	6.616	33.571	3.639	6.616	33.571	4.122	7.495	14.998
3	3.594	6.534	40.106	3.594	6.534	40.106	4.070	7.401	22.398
4	3.421	6.220	46.325	3.421	6.220	46.325	4.063	7.388	29.786
5	3.227	5.867	52.192	3.227	5.867	52.192	4.062	7.386	37.172
6	3.004	5.462	57.654	3.004	5.462	57.654	4.058	7.378	44.550
7	2.885	5.245	62.898	2.885	5.245	62.898	4.049	7.362	51.912
8	2.758	5.014	67.913	2.758	5.014	67.913	4.036	7.337	59.249
9	2.615	4.754	72.667	2.615	4.754	72.667	4.031	7.328	66.578
10	2.580	4.691	77.358	2.580	4.691	77.358	3.996	7.265	73.843
11	2.027	3.685	81.043	2.027	3.685	81.043	3.960	7.200	81.043

Extraction Method: Principal Component Analysis.

In addition, the adequacy of the dataset for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. As presented in Table 8, the KMO value was 0.926, which exceeded the minimum recommended threshold of 0.60 and indicated excellent sampling adequacy. Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 20,050.324$; $df = 1,485$; $p < 0.001$), confirming the existence of sufficient correlations among the measurement items to justify factor analysis.

Table 8. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.926
Approx. Chi-Square		20050.324
Bartlett's Test of Sphericity	Df	1485
	Sig.	0.000

The communalities further demonstrated the adequacy of item representation within the extracted factor structure. All extracted communalities ranged from 0.772 to 0.848, exceeding the minimum acceptable value of 0.50. Specifically, the lowest communality was recorded for AIN5 (0.772),

while ASE1 exhibited the highest communality (0.848). These findings indicate that a substantial proportion of the variance in each observed variable was explained by the extracted factors, confirming the appropriateness of retaining all measurement items. The factor loading criterion was set at 0.60. Results presented in Table 9 showed that all indicators loaded strongly on their respective latent constructs, with loadings ranging from 0.883 to 0.921. For Predictive Data Analytics Capability (PDAC), outer loadings ranged from 0.884 to 0.910. Data Quality and Accessibility (DQA) recorded loadings between 0.888 and 0.921, while Analytics Infrastructure (AIN) ranged from 0.883 to 0.901. Analytical Skills and Expertise (ASE) produced loadings between 0.892 and 0.912, and Predictive Modelling Capability (PMC) recorded values ranging from 0.889 to 0.894. Similarly, all indicators for the mediator and moderator constructs demonstrated satisfactory loadings. Data-Driven Decision-Making (DDDM) recorded loadings ranging from 0.884 to 0.903, while Organizational Analytics Culture (OAC) exhibited loadings between 0.884 and 0.901. The dependent constructs also showed strong measurement properties. Organizational Performance Enhancement (OPE) produced loadings ranging from 0.883 to 0.913. Financial Forecasting Accuracy (FFA) recorded loadings between 0.892 and 0.903, Risk Management Effectiveness (RME) ranged from 0.885 to 0.902, and Operational Efficiency (OEF) exhibited loadings between 0.885 and 0.900.

Table 9. Factor Loading Matrix

Construct Item	Component										
	1	2	3	4	5	6	7	8	9	10	11
PDAC1										0.909	
PDAC2										0.894	
PDAC3										0.910	
PDAC4										0.884	
PDAC5										0.895	
DQA1	0.913										
DQA2	0.888										
DQA3	0.889										

DQA4	0.921	
DQA5	0.903	
AIN1		0.897
AIN2		0.901
AIN3		0.898
AIN4		0.891
AIN5		0.883
ASE1	0.912	
ASE2	0.910	
ASE3	0.892	
ASE4	0.901	
ASE5	0.898	
PMC1		0.894
PMC2		0.893
PMC3		0.894
PMC4		0.889
PMC5		0.891
DDDM1	0.884	
DDDM2	0.903	
DDDM3	0.896	
DDDM4	0.901	
DDDM5	0.901	
OAC1		0.891



OAC2		0.897
OAC3		0.901
OAC4		0.894
OAC5		0.884
OPE1	0.887	
OPE2	0.883	
OPE3	0.899	
OPE4	0.904	
OPE5	0.913	
FFA1		0.900
FFA2		0.894
FFA3		0.892
FFA4		0.901
FFA5		0.903
RME1	0.901	
RME2	0.894	
RME3	0.890	
RME4	0.885	
RME5	0.902	
OEF1		0.897
OEF2		0.885
OEF3		0.900
OEF4		0.900

OEF5

0.894

Since all indicators exceeded the prescribed threshold of 0.70 and no problematic cross-loading issues were observed, no item was removed from the measurement model. The results therefore confirmed satisfactory construct validity and supported the retention of the complete measurement instrument for subsequent PLS-SEM analysis.

4.4 Common Method Bias (CMB) Assessment

The possibility of common method bias was assessed using Harman's Single Factor Test based on Principal Axis Factoring. The results are presented in Table 10. The analysis extracted multiple factors from the dataset, with the first factor accounting for 25.615% of the total variance. This value is substantially below the critical threshold of 50%, which is commonly used as an indication of severe common method bias.

Table 10. Common Method Bias using Harman's Single Factor Analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.826	26.956	26.956	14.088	25.615	25.615
2	3.639	6.616	33.571			
3	3.594	6.534	40.106			
4	3.421	6.220	46.325			
5	3.227	5.867	52.192			
6	3.004	5.462	57.654			
7	2.885	5.245	62.898			
8	2.758	5.014	67.913			
9	2.615	4.754	72.667			
10	2.580	4.691	77.358			

11	2.027	3.685	81.043
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Extraction Method: Principal axis factoring

Based on these findings, common method bias was not considered a significant threat to the validity of the study results. The measurement model therefore demonstrated adequate psychometric properties and was deemed suitable for subsequent reliability, validity, and structural model assessment.

4.5 Assessment of the Measurement Model and Construct Model Fitness Analysis

4.5.1 Convergent Validity Analysis

Convergent validity was assessed using Cronbach's alpha, composite reliability (rho_a and rho_c), and Average Variance Extracted (AVE). Hair et al. (2021) recommend Cronbach's alpha and composite reliability values above 0.70 and AVE values above 0.50 as evidence of satisfactory convergent validity. As presented in Table 11, all constructs recorded Cronbach's alpha values ranging from 0.936 to 0.943, exceeding the recommended threshold of 0.70. Similarly, composite reliability (rho_c) values ranged from 0.951 to 0.957, indicating strong internal consistency reliability. The AVE values ranged between 0.796 and 0.815, which are substantially higher than the minimum threshold of 0.50. These results confirm that the indicators adequately explained their respective latent constructs and that convergent validity was established for all study variables.

Table 11. Construct Reliability and Convergent Validity Assessment

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
Analytical Skills and Expertise	0.943	0.946	0.956	0.815
Analytics Infrastructure	0.937	0.940	0.952	0.800
Data Quality and Accessibility	0.943	0.949	0.957	0.815
Data-Driven Decision-Making	0.939	0.940	0.954	0.805
Financial Forecasting Accuracy	0.940	0.941	0.954	0.806
Operational Efficiency	0.938	0.940	0.953	0.801

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	AVE
Organizational Analytics Culture	0.937	0.938	0.952	0.798
Organizational Performance Enhancement	0.939	0.941	0.954	0.805
Predictive Data Analytics Capability	0.940	0.942	0.954	0.807
Predictive Modelling Capability	0.936	0.938	0.951	0.796
Risk Management Effectiveness	0.938	0.939	0.952	0.800

Discriminant Validity Analysis

Discriminant validity was assessed using both the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker criterion. HTMT values below 0.85 indicate adequate discriminant validity.

The HTMT results presented in Table 12 show that all values ranged from 0.012 to 0.442, well below the threshold of 0.85. The highest HTMT value observed was 0.442 between Predictive Data Analytics Capability and Data-Driven Decision-Making. Since all values remained substantially below the recommended cut-off point, the constructs demonstrated satisfactory discriminant validity and were empirically distinct from one another.

Table 12. Heterotrait-Monotrait Ratio (HTMT) Matrix

Constructs	ASE	AIN	DQA	DDDM	FFA	OEF	OAC	OPE	PDAC	PMC	RME
ASE	-										
AIN	0.169	-									

Constructs	ASE	AIN	DQA	DDDM	FFA	OEF	OAC	OPE	PDAC	PMC	RME
DQA	0.220	0.277	-								
DDDM	0.280	0.288	0.268	-							
FFA	0.235	0.316	0.248	0.294	-						
OEF	0.301	0.268	0.288	0.218	0.297	-					
OAC	0.343	0.329	0.354	0.305	0.315	0.279	-				
OPE	0.294	0.282	0.250	0.270	0.220	0.247	0.298	-			
PDAC	0.303	0.279	0.262	0.442	0.346	0.320	0.442	0.256	-		
PMC	0.236	0.257	0.264	0.287	0.322	0.290	0.259	0.211	0.308	-	
RME	0.273	0.342	0.258	0.252	0.268	0.245	0.307	0.304	0.300	0.250	-

Key: ASE = Analytical Skills and Expertise; AIN = Analytics Infrastructure; DQA = Data Quality and Accessibility; DDDM = Data-Driven Decision-Making; FFA = Financial Forecasting Accuracy; OEF = Operational Efficiency; OAC = Organizational Analytics Culture; OPE = Organizational Performance Enhancement; PDAC = Predictive Data Analytics Capability; PMC = Predictive Modelling Capability; RME = Risk Management Effectiveness.

The HTMT values ranged from 0.169 to 0.442, which were all below the recommended threshold of 0.85. The highest HTMT value was observed between Predictive Data Analytics Capability and Data-Driven Decision-Making (HTMT = 0.442), as well as between Predictive Data Analytics Capability and Organizational Analytics Culture (HTMT = 0.442). These findings indicate adequate discriminant validity among all constructs. Furthermore, the Fornell-Larcker criterion results in Table 13 indicate that the square root of the AVE for each construct was greater than its correlations with other constructs. For example, Predictive Data Analytics Capability recorded a square root AVE value of 0.898, which exceeded its highest correlation with Data-Driven Decision-Making (0.416). Similar patterns were observed across all constructs. These findings further confirm the establishment of discriminant validity.

Table 13. Fornell-Larcker Criterion Matrix

Constructs	ASE	AIN	DQA	DDDM	FFA	OEF	OAC	OPE	PDAC	PMC	RME
ASE	0.903										
AIN	0.161	0.894									
DQA	0.208	0.262	0.903								
DDDM	0.265	0.272	0.253	0.897							
FFA	0.223	0.298	0.236	0.276	0.898						
OEF	0.285	0.254	0.273	0.206	0.279	0.895					
OAC	0.324	0.310	0.332	0.286	0.295	0.262	0.893				
OPE	0.277	0.266	0.238	0.255	0.207	0.230	0.280	0.897			
PDAC	0.289	0.263	0.249	0.416	0.325	0.301	0.414	0.241	0.898		
PMC	0.221	0.240	0.249	0.269	0.303	0.274	0.241	0.196	0.291	0.892	
RME	0.259	0.324	0.245	0.236	0.252	0.228	0.286	0.287	0.282	0.235	0.895

Note: Diagonal values shown in bold represent the square root of the Average Variance Extracted (AVE) for each construct.

The Fornell-Larcker criterion results show that the square root of the AVE for every construct exceeded its corresponding inter-construct correlations. For example, Predictive Data Analytics Capability recorded a square root AVE value of 0.898, which was greater than its highest correlation with Data-Driven Decision-Making (0.416). Similarly, Data Quality and Accessibility recorded a square root AVE value of 0.903, exceeding all associated correlation coefficients. These results provide additional evidence that discriminant validity was satisfactorily established. The results indicate that each construct shared more variance with its own indicators than with other constructs in the model.

4.6 Collinearity Assessment

Collinearity was assessed using the Variance Inflation Factor (VIF). Hair et al. (2021) recommend VIF values below 5.0, while values below 3.3 are considered highly satisfactory. As shown in

Table 14, all VIF values ranged from 1.000 to 1.377. The highest value was recorded for the relationship between Predictive Data Analytics Capability and Organizational Performance Enhancement (VIF = 1.377). Since all values were considerably below the critical threshold, multicollinearity was not a concern in the structural model.

Table 14. Collinearity Assessment (VIF)

Structural Relationship	VIF
Predictive Data Analytics Capability → Organizational Performance Enhancement	1.377
Organizational Analytics Culture → Organizational Performance Enhancement	1.247
Data-Driven Decision-Making → Organizational Performance Enhancement	1.233
Data Quality and Accessibility → Financial Forecasting Accuracy	1.141
Predictive Modelling Capability → Financial Forecasting Accuracy	1.135
Analytics Infrastructure → Financial Forecasting Accuracy	1.120
Analytical Skills and Expertise → Financial Forecasting Accuracy	1.087
Lowest Observed VIF	1.000

The findings suggest the absence of collinearity problems and confirm the suitability of the data for structural model estimation.

4.7 Model Predictive Power and Relevance Analysis

4.7.1 Coefficient of Determination (R^2)

The R^2 values indicate the proportion of variance explained by the predictor variables. As presented in Table 15, Predictive Data Analytics Capability recorded the highest explanatory power ($R^2 = 0.181$), followed by Operational Efficiency ($R^2 = 0.178$), Risk Management Effectiveness ($R^2 = 0.177$), Financial Forecasting Accuracy ($R^2 = 0.174$), Data-Driven Decision-Making ($R^2 = 0.173$), and Organizational Performance Enhancement ($R^2 = 0.120$). These findings indicate that the model explained between 12.0% and 18.1% of the variance in the endogenous constructs, representing modest but acceptable explanatory power for organizational and behavioural research.

Table 15. Coefficient of Determination (R^2) Results

Endogenous Construct	R ²	Adjusted R ²
Predictive Data Analytics Capability	0.181	0.173
Operational Efficiency	0.178	0.169
Risk Management Effectiveness	0.177	0.169
Financial Forecasting Accuracy	0.174	0.165
Data-Driven Decision-Making	0.173	0.171
Organizational Performance Enhancement	0.120	0.111

4.7.2 Effect Size (f^2) Analysis

The effect size analysis assessed the contribution of each predictor to the explained variance of the endogenous constructs. Cohen's guidelines classify f^2 values of 0.02, 0.15, and 0.35 as small, medium, and large effects respectively. As shown in Table 16, Predictive Data Analytics Capability exerted the strongest influence on Data-Driven Decision-Making ($f^2 = 0.209$), representing a medium effect size. All other significant relationships recorded small effect sizes ranging from 0.008 to 0.062. Analytics Infrastructure demonstrated the strongest contribution to Risk Management Effectiveness ($f^2 = 0.062$), while Analytical Skills and Expertise had notable effects on Predictive Data Analytics Capability ($f^2 = 0.044$) and Operational Efficiency ($f^2 = 0.042$). The moderating effect of Organizational Analytics Culture on the relationship between Predictive Data Analytics Capability and Organizational Performance Enhancement recorded a very small effect size ($f^2 = 0.002$).

Table 16. Effect Size (f^2) Results

Relationship	f^2
Predictive Data Analytics Capability → Data-Driven Decision-Making	0.209
Analytics Infrastructure → Risk Management Effectiveness	0.062
Analytical Skills and Expertise → Predictive Data Analytics Capability	0.044
Analytics Infrastructure → Financial Forecasting Accuracy	0.044

Relationship	f ²
Predictive Modelling Capability → Financial Forecasting Accuracy	0.043
Analytical Skills and Expertise → Operational Efficiency	0.042
Organizational Analytics Culture → Organizational Performance Enhancement	0.037
All Remaining Relationships	0.002 – 0.035

The results indicate that Data-Driven Decision-Making received the greatest substantive contribution from Predictive Data Analytics Capability, while most other relationships exerted small but meaningful effects.

4.8 Model Fitness Analysis

Model fit was assessed using the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), d_ ULS, and d_ G statistics. The findings presented in Table 17 show that the saturated model recorded an SRMR value of 0.031, while the estimated model produced an SRMR value of 0.081. Both values fall within acceptable limits, indicating adequate model fit. Hair et al. (2021) suggest that SRMR values below 0.08 indicate a good fit, while values close to this threshold remain acceptable in exploratory predictive models. The NFI values were 0.902 for the saturated model and 0.897 for the estimated model. These values are close to the recommended benchmark of 0.90, indicating satisfactory model fit.

Table 17. Model Fit Assessment

Fit Index	Saturated Model	Estimated Model
SRMR	0.031	0.081
d_ ULS	1.444	10.183
d_ G	0.886	0.952

Fit Index	Saturated Model	Estimated Model
Chi-Square	2066.027	2179.084
NFI	0.902	0.897

Consequently, it can be concluded that the reliability, validity, predictive power, collinearity diagnostics, and model fit statistics collectively confirmed that the measurement and structural models were statistically adequate and suitable for hypothesis testing, mediation analysis, moderation analysis, and subsequent fsQCA assessment.

4.9 Structural Model and Hypothesis Path Analysis Results

4.9.1 *The Influence of Predictive Data Analytics Capability on Financial Forecasting Accuracy, Risk Management Effectiveness, and Operational Efficiency*

The second objective of the study sought to find out the influence of predictive data analytics capability on financial forecasting accuracy, risk management effectiveness, and operational efficiency among SMEs in the FMCG industry in the United States. The analysis examined the effects of four dimensions of predictive data analytics capability, namely data quality and accessibility, analytics infrastructure, analytical skills and expertise, and predictive modelling capability. The findings were assessed using the path coefficients (β), sample means (M), standard deviations (SD), t-statistics, and p-values. A relationship was considered statistically significant where the p-value was below 0.05, with a positive path coefficient indicating a positive influence between the variables.

The results show that data quality and accessibility had a significant positive effect on financial forecasting accuracy ($\beta = 0.108$, $M = 0.109$, $SD = 0.049$, $t = 2.221$, $p = 0.026$). The positive coefficient indicates that improvements in the quality and accessibility of data are associated with improvements in the accuracy of financial forecasts. Although the effect was statistically significant, its relatively small coefficient indicates a modest predictive effect compared with some of the other dimensions examined. In practical terms, SMEs with more reliable, accessible and usable data tend to achieve more accurate financial forecasts. Since the p-value of 0.026 is below the 0.05 significance level and the t-value of 2.221 exceeds the commonly applied threshold of 1.96, the relationship is statistically supported. Therefore, the hypothesis that Data Quality and Accessibility has a significant positive effect on Financial Forecasting Accuracy among SMEs in the FMCG industry in the United States is accepted. Similarly, analytics infrastructure demonstrated a significant positive effect on financial forecasting accuracy ($\beta = 0.202$, $M = 0.203$, $SD = 0.050$, $t = 4.034$, $p < 0.001$). This was a stronger effect than that observed for data quality and accessibility. The positive path coefficient indicates that stronger analytics infrastructure is associated with greater financial forecasting accuracy. The result suggests that the availability of

appropriate systems, technologies and computing infrastructure provides SMEs with a stronger basis for processing data and generating accurate forecasts. The t-value of 4.034 and p-value below 0.001 provide strong statistical evidence of the relationship. Therefore, the hypothesis that Analytics Infrastructure has a significant positive effect on Financial Forecasting Accuracy among SMEs in the FMCG industry in the United States is accepted. Analytical skills and expertise also had a significant positive effect on financial forecasting accuracy ($\beta = 0.123$, $M = 0.123$, $SD = 0.046$, $t = 2.677$, $p = 0.007$). The result indicates that SMEs with stronger analytical knowledge and expertise tend to achieve better financial forecasting outcomes. Although the effect is relatively modest, its statistical significance shows that the human capability to understand, analyze and interpret data contributes to the quality of financial forecasts. The p-value of 0.007 is below 0.05, while the t-value of 2.677 exceeds 1.96. Therefore, the hypothesis that Analytical Skills and Expertise has a significant positive effect on Financial Forecasting Accuracy among SMEs in the FMCG industry in the United States is accepted.

Predictive modelling capability produced a significant positive effect on financial forecasting accuracy and recorded one of the stronger effects among the four dimensions ($\beta = 0.200$, $M = 0.200$, $SD = 0.050$, $t = 4.032$, $p < 0.001$). The result indicates that greater ability to develop and apply predictive models is associated with improved accuracy in financial forecasts. The coefficient of 0.200 shows a positive predictive relationship of substantial strength relative to the other dimensions in this part of the model. The very low p-value and t-value of 4.032 provide strong evidence that the relationship is not due to sampling variation. Therefore, the hypothesis that Predictive Modelling Capability has a significant positive effect on Financial Forecasting Accuracy among SMEs in the FMCG industry in the United States is accepted. Taken together, the results show that all four dimensions of predictive data analytics capability significantly and positively influence financial forecasting accuracy, with analytics infrastructure ($\beta = 0.202$) and predictive modelling capability ($\beta = 0.200$) showing the strongest effects. The analysis further examined whether the four dimensions of predictive data analytics capability influence risk management effectiveness. The results indicate that data quality and accessibility had a significant positive effect on risk management effectiveness ($\beta = 0.120$, $M = 0.120$, $SD = 0.048$, $t = 2.513$, $p = 0.012$). This finding suggests that access to reliable and relevant data improves SMEs' ability to identify and respond to potential risks. The positive coefficient indicates that improvements in data quality and accessibility are associated with stronger risk management outcomes. Since the p-value of 0.012 is below 0.05 and the t-value of 2.513 exceeds 1.96, the relationship is statistically significant. Therefore, the hypothesis that Data Quality and Accessibility has a significant positive effect on Risk Management Effectiveness among SMEs in the FMCG industry in the United States is accepted. Analytics infrastructure recorded the strongest effect on risk management effectiveness among the four predictive data analytics capability dimensions ($\beta = 0.239$, $M = 0.241$, $SD = 0.047$, $t = 5.094$, $p < 0.001$). The positive path coefficient indicates that stronger analytics infrastructure is associated with better risk management effectiveness. The relatively

larger coefficient suggests that the technological capacity to collect, process and analyse information is particularly important for enabling SMEs to identify and manage risks. The t-value of 5.094 provides strong evidence of the relationship, while the p-value below 0.001 confirms statistical significance. Therefore, the hypothesis that Analytics Infrastructure has a significant positive effect on Risk Management Effectiveness among SMEs in the FMCG industry in the United States is accepted. Analytical skills and expertise also had a significant positive effect on risk management effectiveness ($\beta = 0.172$, $M = 0.172$, $SD = 0.052$, $t = 3.326$, $p = 0.001$). This finding indicates that the ability of employees to understand and apply analytical information contributes positively to the firm's capacity to manage risks. The effect is stronger than the corresponding effect of analytical skills on financial forecasting accuracy, suggesting that analytical expertise is particularly relevant when firms need to interpret information and identify potential threats to business activities. With a t-value of 3.326 and a p-value of 0.001, the relationship is statistically significant. Therefore, the hypothesis that Analytical Skills and Expertise has a significant positive effect on Risk Management Effectiveness among SMEs in the FMCG industry in the United States is accepted.

Predictive modelling capability likewise had a significant positive effect on risk management effectiveness ($\beta = 0.110$, $M = 0.110$, $SD = 0.045$, $t = 2.455$, $p = 0.014$). The positive coefficient indicates that stronger predictive modelling capability is associated with improved ability to manage risks. This suggests that SMEs that are better able to use predictive models can identify possible risk conditions in advance and support more informed risk responses. Although the coefficient is relatively modest, the relationship remains statistically significant because the p-value is below 0.05 and the t-value is above 1.96. Therefore, the hypothesis that Predictive Modelling Capability has a significant positive effect on Risk Management Effectiveness among SMEs in the FMCG industry in the United States is accepted. Collectively, the findings show that all four dimensions of predictive data analytics capability have significant positive effects on risk management effectiveness, with analytics infrastructure producing the strongest effect ($\beta = 0.239$), followed by analytical skills and expertise ($\beta = 0.172$), data quality and accessibility ($\beta = 0.120$), and predictive modelling capability ($\beta = 0.110$). The findings also demonstrate significant positive relationships between all four dimensions of predictive data analytics capability and operational efficiency. Data quality and accessibility had a significant positive effect on operational efficiency ($\beta = 0.155$, $M = 0.157$, $SD = 0.049$, $t = 3.169$, $p = 0.002$). This finding indicates that SMEs with better access to accurate and usable data are better positioned to improve their operational processes. Reliable data can support more informed resource allocation and reduce delays and errors in operational decisions. The p-value of 0.002 and t-value of 3.169 confirm that the relationship is statistically significant. Therefore, the hypothesis that Data Quality and Accessibility has a significant positive effect on Operational Efficiency among SMEs in the FMCG industry in the United States is accepted. Analytics infrastructure also had a significant positive effect on operational efficiency ($\beta = 0.144$, $M = 0.143$, $SD = 0.047$, $t = 3.067$, $p = 0.002$). The

result suggests that appropriate analytical systems and technological infrastructure support more efficient business processes. Although the coefficient is smaller than the effect of analytics infrastructure on financial forecasting accuracy and risk management effectiveness, it remains statistically significant. The p-value of 0.002 is below 0.05 and the t-value of 3.067 exceeds the required threshold. Therefore, the hypothesis that Analytics Infrastructure has a significant positive effect on Operational Efficiency among SMEs in the FMCG industry in the United States is accepted. Analytical skills and expertise produced a somewhat stronger positive effect on operational efficiency ($\beta = 0.195$, $M = 0.195$, $SD = 0.046$, $t = 4.261$, $p < 0.001$). This finding indicates that employees' ability to analyse and interpret information is an important contributor to efficient operations. The relatively high coefficient suggests that the effective use of analytical information depends not only on technological resources but also on the skills available within the organisation. The t-value of 4.261 and p-value below 0.001 provide strong statistical support for the relationship. Therefore, the hypothesis that Analytical Skills and Expertise has a significant positive effect on Operational Efficiency among SMEs in the FMCG industry in the United States is accepted.

Finally, predictive modelling capability had a significant positive effect on operational efficiency ($\beta = 0.158$, $M = 0.159$, $SD = 0.048$, $t = 3.260$, $p = 0.001$). The finding suggests that the ability to use predictive models contributes to more efficient operations by helping SMEs anticipate conditions that may affect resources, processes and business activities. The relationship is statistically significant, as shown by the p-value of 0.001 and t-value of 3.260. Therefore, the hypothesis that Predictive Modelling Capability has a significant positive effect on Operational Efficiency among SMEs in the FMCG industry in the United States is accepted. Across the four dimensions, analytical skills and expertise recorded the strongest effect on operational efficiency ($\beta = 0.195$), followed by predictive modelling capability ($\beta = 0.158$), data quality and accessibility ($\beta = 0.155$), and analytics infrastructure ($\beta = 0.144$). Clearly, the findings provide consistent evidence that the four dimensions of predictive data analytics capability positively influence the three outcomes examined. For financial forecasting accuracy, analytics infrastructure and predictive modelling capability produced the strongest effects. For risk management effectiveness, analytics infrastructure was clearly the strongest predictor, while for operational efficiency, analytical skills and expertise recorded the largest coefficient. Hence, the relative importance of the dimensions varies according to the organizational outcome being considered. Importantly, all twelve hypothesized relationships were statistically significant and positive, with p-values ranging from less than 0.001 to 0.026 and t-values ranging from 2.221 to 5.094 (Table 18).

Table 18. Hypothesis Decision for the Effects of PDAC Dimensions on FFA, RME and OEF

Hypothesis	Relationship	β (Path Coefficient)	Mean	SD	T-value	p-value	Decision
H1	DQA $\rightarrow$ FFA	0.108	0.109	0.049	2.221	0.026	Accepted
H2	AIN $\rightarrow$ FFA	0.202	0.203	0.050	4.034	0.000	Accepted
H3	ASE $\rightarrow$ FFA	0.123	0.123	0.046	2.677	0.007	Accepted
H4	PMC $\rightarrow$ FFA	0.200	0.200	0.050	4.032	0.000	Accepted
H5	DQA $\rightarrow$ RME	0.120	0.120	0.048	2.513	0.012	Accepted
H6	AIN $\rightarrow$ RME	0.239	0.241	0.047	5.094	0.000	Accepted
H7	ASE $\rightarrow$ RME	0.172	0.172	0.052	3.326	0.001	Accepted
H8	PMC $\rightarrow$ RME	0.110	0.110	0.045	2.455	0.014	Accepted
H9	DQA $\rightarrow$ OEF	0.155	0.157	0.049	3.169	0.002	Accepted
H10	AIN $\rightarrow$ OEF	0.144	0.143	0.047	3.067	0.002	Accepted
H11	ASE $\rightarrow$ OEF	0.195	0.195	0.046	4.261	0.000	Accepted
H12	PMC $\rightarrow$ OEF	0.158	0.159	0.048	3.260	0.001	Accepted

4.9.2 The Mediating role of Data Driven Decision Making in the Relationship between Predictive Data Analytics Capability and Organizational Performance Enhancement

The third objective of the study sought to examine the mediating role of Data-Driven Decision-Making (DDDM) and the moderating role of Organizational Analytics Culture (OAC) in the relationship between Predictive Data Analytics Capability (PDAC) and Organizational Performance Enhancement (OPE) among SMEs in the FMCG industry in the United States. The analysis therefore focuses on whether DDDM explains the relationship between PDAC and OPE and whether OAC changes the strength of the relationship between PDAC and OPE. The mediation analysis examined whether DDDM provides a pathway through which PDAC contributes to OPE. The specific indirect effect of PDAC on OPE through DDDM was positive and statistically significant ($\beta = 0.067$, mean = 0.066, SD = 0.022, T = 3.007, p = 0.003). This indicates that PDAC

has a positive indirect effect on OPE through DDDM. In practical terms, the path coefficient of 0.067 indicates that a one-unit increase in PDAC is associated with a 0.067-unit increase in OPE through the DDDM pathway, representing a positive but relatively modest indirect effect. The result also shows that the link between PDAC and DDDM is statistically significant, while the resulting pathway contributes significantly to OPE. The significance of the indirect effect is particularly important because mediation is established by demonstrating that the predictor influences the mediator and that the indirect pathway from the predictor through the mediator to the outcome is significant. The findings therefore indicate that SMEs with stronger PDAC are more likely to use data-driven decision-making, which in turn contributes to improved organizational performance.

Further evidence is provided by the direct relationship between PDAC and OPE. The direct path was positive but did not reach the 5% significance level ($\beta = 0.098$, mean = 0.098, SD = 0.053, $T = 1.857$, $p = 0.063$). Thus, although PDAC has a positive direct relationship with OPE, the direct effect is not statistically significant. When considered alongside the significant indirect effect through DDDM, the findings suggest that the contribution of PDAC to organizational performance operates mainly through the use of data-driven decision-making rather than through a statistically significant direct pathway. Therefore, the hypothesis that DDDM mediates the relationship between PDAC and OPE among SMEs in the FMCG industry in the United States is accepted. The supporting paths also show that the different dimensions of PDAC contribute to DDDM. ASE had a significant positive indirect relationship with DDDM ($\beta = 0.083$, mean = 0.083, SD = 0.021, $T = 3.948$, $p < 0.001$), followed by PMC ($\beta = 0.075$, mean = 0.075, SD = 0.023, $T = 3.261$, $p = 0.001$), AIN ($\beta = 0.065$, mean = 0.065, SD = 0.023, $T = 2.880$, $p = 0.004$), and DQA ($\beta = 0.051$, mean = 0.052, SD = 0.022, $T = 2.305$, $p = 0.021$). These results indicate that analytical expertise, predictive modelling capability, analytics infrastructure, and data quality and accessibility all contribute positively to data-driven decision-making. Among these dimensions, ASE shows the strongest effect on DDDM, while DQA records the weakest. This pattern further supports the mediating role of DDDM because the different capability dimensions are able to strengthen the decision-making process through which analytics can contribute to organizational outcomes. The specific indirect effects provide additional evidence, although the strength of the mediation pathway varies across the PDAC dimensions. The indirect effect from AIN through PDAC and DDDM to OPE was significant ($\beta = 0.010$, mean = 0.010, SD = 0.005, $T = 2.064$, $p = 0.039$), as was the corresponding effect for ASE ($\beta = 0.013$, mean = 0.013, SD = 0.005, $T = 2.454$, $p = 0.014$) and PMC ($\beta = 0.012$, mean = 0.012, SD = 0.005, $T = 2.213$, $p = 0.027$). However, the corresponding pathway for DQA was not statistically significant ($\beta = 0.008$, mean = 0.008, SD = 0.004, $T = 1.874$, $p = 0.061$). This suggests that the contribution of analytics capability to organizational performance through DDDM is stronger for analytics infrastructure, analytical skills and expertise, and predictive modelling capability, whereas the indirect pathway involving data quality and accessibility is not statistically supported at the 5% level.

4.9.3 The Moderating Role of Organizational Analytics Culture in the Relationship Between Predictive Data Analytics Capability and Organizational Performance Enhancement

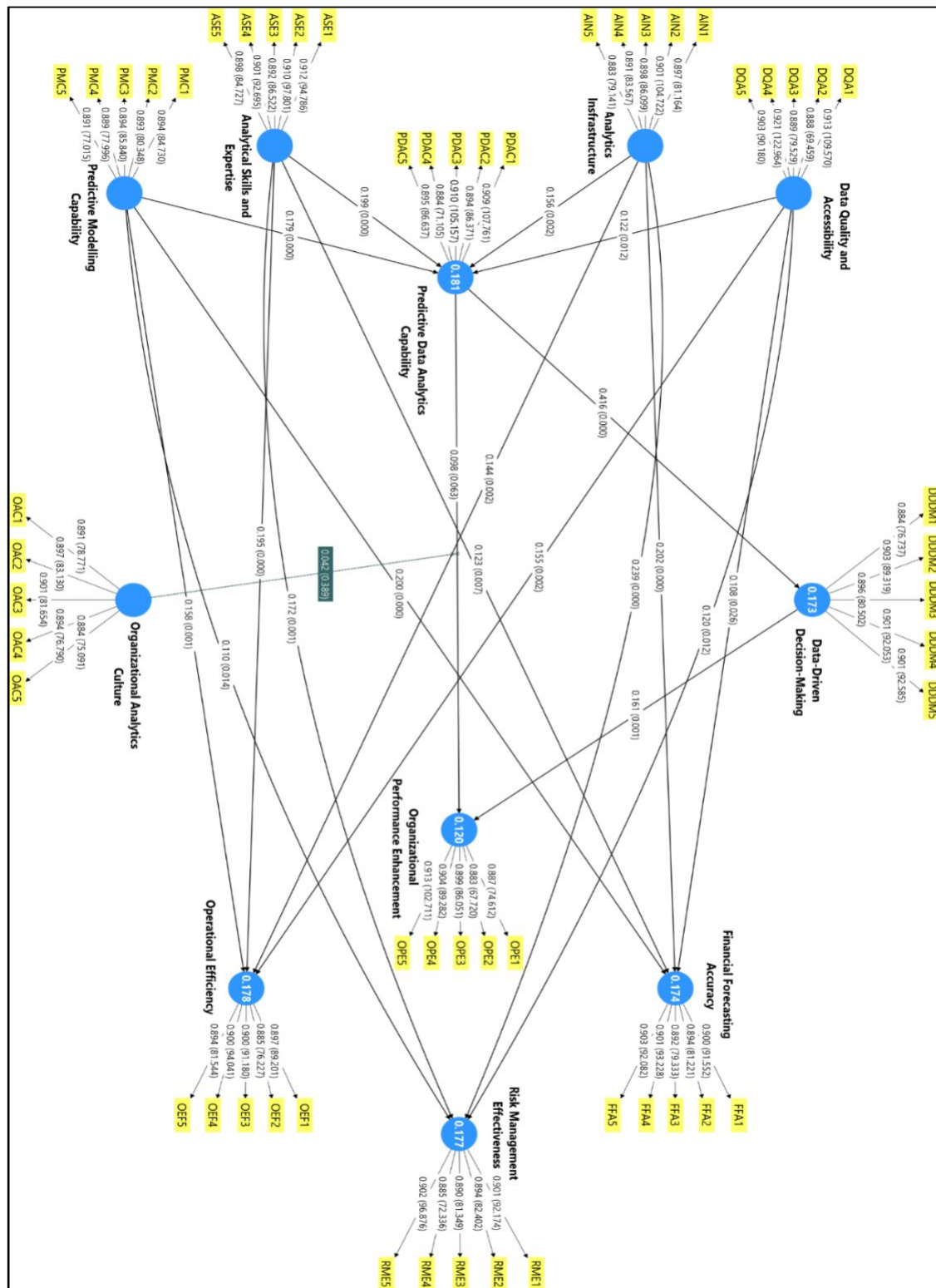
The moderation analysis examined whether OAC changes the strength of the relationship between PDAC and OPE. The interaction term between OAC and PDAC was positive but statistically insignificant ($\beta = 0.042$, mean = 0.044, SD = 0.049, $T = 0.862$, $p = 0.389$). Although the positive coefficient suggests that OAC may have a positive direction of influence on the PDAC–OPE relationship, the very small path coefficient and the non-significant p-value indicate that the effect is not strong enough to establish a moderating relationship in the sample. The result means that differences in OAC do not significantly change the effect of PDAC on OPE among the SMEs studied. In other words, having a stronger organizational culture that supports analytics does not, based on the findings, significantly strengthen the relationship between PDAC and organizational performance. This finding is also consistent with the direct relationship between OAC and OPE, which was positive and significant ($\beta = 0.201$, mean = 0.204, SD = 0.051, $T = 3.963$, $p < 0.001$). Thus, OAC itself is associated with better organizational performance, but it does not significantly alter the strength of the relationship between PDAC and OPE. Similarly, PDAC had a positive but statistically insignificant direct effect on OPE ($\beta = 0.098$, mean = 0.098, SD = 0.053, $T = 1.857$, $p = 0.063$). Therefore, the findings suggest that OAC functions more as a direct organizational factor associated with OPE than as a condition that strengthens the effect of PDAC on OPE. Consequently, the hypothesis that OAC positively moderates the relationship between PDAC and OPE among SMEs in the FMCG industry in the United States is not supported and is therefore rejected.

Table 19. Hypothesis Testing for the Mediating and Moderating Effects

Hypothesis	Relationship/Effect	β	Mean	SD	T-value	p-value	Decision
H13	PDAC $\rightarrow$ DDDM $\rightarrow$ OPE	0.067	0.066	0.022	3.007	0.003	Accepted
H14	PDAC $\times$ OAC $\rightarrow$ OPE	0.042	0.044	0.049	0.862	0.389	Rejected

The structural model and path analysis results for the entire study variable construct relationships are shown in Figure 2.

Figure 2. Structural Model and Path Analysis Results



4.9.4 Fuzzy-set Qualitative Comparative Analysis (fsQCA) of Predictive Data Analytics Capability and Organizational Performance Enhancement

Following the PLS-SEM analysis, fsQCA was employed as a complementary analytical technique to examine how different combinations of predictive analytics capabilities, organizational conditions, and decision-making practices jointly contributed to organizational performance outcomes. Unlike symmetric techniques that estimate net effects, fsQCA recognizes that multiple pathways may lead to the same outcome and allows the identification of complex causal configurations associated with high organizational performance.

4.10 Contrarian Case Analysis

Before conducting calibration and configurational analyses, a contrarian case analysis was performed. All study variables were divided into quintiles and cross-tabulated against organizational performance outcomes. The purpose was to determine whether cases existed that contradicted the overall positive relationships observed in the PLS-SEM results. The findings revealed statistically significant positive associations across all variable combinations. However, several contrarian cases were also identified. These cases occurred where firms with low levels of predictive analytics capabilities recorded high performance outcomes, and where firms with high capability levels reported relatively low outcomes. The existence of such cases justified the application of fsQCA because they indicated that causal complexity and equifinality were present within the dataset.

Table 20. Summary of Contrarian Case Analysis

Variable Relationship	Contrarian Cases Observed	Kendall's Tau-c	Cramer's V	p-value
PDAC → OPE	21 cases (Low PDAC; High OPE), 6 cases (High PDAC; Low OPE)	0.157	0.143	<0.001
PDAC → FFA	13 cases (Low PDAC; High FFA), 7 cases (High PDAC; Low FFA)	0.203	0.165	<0.001
PDAC → RME	16 cases (Low PDAC; High RME), 8 cases (High PDAC; Low RME)	0.218	0.161	<0.001
PDAC → OEF	13 cases (Low PDAC; High OEF), 4 cases (High PDAC; Low OEF)	0.236	0.175	<0.001

Variable Relationship	Contrarian Cases Observed	Kendall's Tau-c	Cramer's V	p-value
DQA → OPE	20 cases (Low DQA; High OPE), 7 cases (High DQA; Low OPE)	0.189	0.163	<0.001
AIN → OPE	19 cases (Low AIN; High OPE), 7 cases (High AIN; Low OPE)	0.177	0.132	<0.001
ASE → OPE	19 cases (Low ASE; High OPE), 8 cases (High ASE; Low OPE)	0.168	0.165	<0.001
PMC → OPE	18 cases (Low PMC; High OPE), 3 cases (High PMC; Low OPE)	0.101	0.121	0.011
DDDM → OPE	24 cases (Low DDDM; High OPE), 4 cases (High DDDM; Low OPE)	0.174	0.167	<0.001
OAC → OPE	20 cases (Low OAC; High OPE), 8 cases (High OAC; Low OPE)	0.191	0.146	<0.001

Source: Field Survey Data (2026)

Table 20 shows clear evidence of contrarian observations across all relationships. For instance, within the PDAC-OPE relationship, 21 firms located in the lowest predictive analytics capability quintile were found in the fourth organizational performance quintile, while 6 firms in the highest PDAC quintile appeared in the lowest OPE quintile. Similar patterns emerged across DQA, AIN, ASE, PMC, DDDM, and OAC. The statistically significant Kendall's Tau-c coefficients, ranging from 0.101 to 0.236, confirmed positive monotonic relationships. Nevertheless, the presence of noticeable off-diagonal frequencies demonstrated that organizational performance was not determined by a single factor operating independently. These findings provided empirical support for conducting fsQCA to identify combinations of conditions associated with high performance outcomes.

4.11 Data Preparation and Calibration

Data preparation and calibration were conducted sequentially using SPSS and fsQCA to ensure that all study constructs were appropriately transformed into fuzzy-set measures suitable for configurational analysis. Attention was placed on maintaining consistency across constructs, preserving empirical variation, and establishing clear anchors for set membership that would

support robust necessary and sufficient condition analyses in subsequent stages. Initial data preparation was undertaken in SPSS. All study variables were first screened to confirm completeness and suitability for calibration. The dataset contained 400 valid cases for each construct, with no missing values recorded. Descriptive statistics were subsequently generated to derive the empirical anchors required for fuzzy-set calibration. Specifically, the 5th, 50th, and 95th percentiles were computed for all variables and exported for use in fsQCA. These percentile values served as the thresholds for full non-membership, crossover, and full membership respectively, consistent with established fsQCA practice.

Table 21. Percentile Statistics Used for Fuzzy-Set Calibration of Study Constructs (N = 400)

Construct	5 th Percentile (Full Non-membership)	50 th Percentile (Crossover)	95 th Percentile (Full Membership)
PDAC	1.8000	3.6000	5.0000
DQA	1.8000	3.6000	5.0000
AIN	1.8000	3.6000	5.0000
ASE	1.8000	3.6000	5.0000
PMC	2.0000	3.6000	5.0000
DDDM	2.0000	3.6000	5.0000
OAC	1.8100	3.6000	5.0000
OPE	2.0000	3.6000	5.0000
FFA	2.0000	3.6000	5.0000
RME	1.8100	3.6000	5.0000
OEF	2.0000	3.6667	5.0000

Source: Field Survey Data (2026)

As shown in Table 21, the calibration anchors displayed considerable consistency across constructs. Most variables recorded full non-membership thresholds between 1.80 and 2.00, crossover values around 3.60, and full membership thresholds at 5.00. These values reflected the empirical distribution of respondents' perceptions and provided suitable benchmarks for distinguishing low, moderate, and high levels of each condition. Following the derivation of percentile anchors, the dataset was transferred to fsQCA for calibration. Each construct was transformed into a fuzzy set using the direct calibration method, with the 5th percentile representing full non-membership, the 50th percentile representing the crossover point, and the 95th percentile representing full membership. The software converted raw scores into membership values ranging from 0 to 1 through a log-odds transformation procedure. Special attention was given to observations positioned exactly at the crossover threshold of 0.50. Cases at this point represent maximum ambiguity in set membership and may be excluded automatically during truth table construction. To prevent potential loss of information, a small constant of 0.001 was added to calibrated scores located at or below the crossover point. This adjustment ensured that all observations were retained for subsequent analyses while minimizing the possibility of analytical distortions. The calibration process also involved systematic recoding of variables. Calibrated variables were initially assigned the prefix "C" to distinguish them from raw measures. After applying the 0.001 adjustment, the prefix "A" was added to identify the final calibrated measures used in the necessary condition and sufficiency analyses. This calibration procedure produced well-defined fuzzy sets and provided a robust foundation for the subsequent configurational analyses.

4.12 Necessary Condition Analysis (NCA)

The necessary condition analysis was conducted separately for each outcome variable in accordance with the study's structural model. Following recommended fsQCA procedures, the frequency threshold was fixed at three cases and the minimum consistency threshold was set at 0.75. Table 22 presents the necessity analysis results.

Table 22. Necessary Condition Analysis Results

Outcome	Condition	Consistency	Coverage	Necessary Condition
ACFFA	ACDQA	0.697	0.690	No
	ACAIN	0.734	0.693	No
	ACASE	0.712	0.683	No

Outcome	Condition	Consistency	Coverage	Necessary Condition
ACRME	ACPMC	0.691	0.700	No
	ACDQA	0.711	0.700	No
	ACAIN	0.742	0.696	No
	ACASE	0.724	0.691	No
ACOE	ACPMC	0.688	0.692	No
	ACDQA	0.709	0.704	No
	ACAIN	0.730	0.690	No
	ACASE	0.721	0.693	No
ACOE	ACPMC	0.688	0.698	No
	ACPDAC + ACDDDM	0.830	0.660	Yes
	ACPDAC	0.697	0.695	No
	ACDDDM	0.692	0.703	No
	ACPDAC + ACOAC	0.832	0.662	Yes

Source: Field Survey Data (2026)

The results in Table 22 show that none of the individual antecedent conditions achieved the recommended consistency threshold of 0.75 for financial forecasting accuracy (ACFFA), risk management effectiveness (ACRME), or operational efficiency (ACOE). The highest consistency values were observed for analytics infrastructure (ACAIN) in relation to ACRME (Consistency = 0.742), ACFFA (Consistency = 0.734), and ACOE (Consistency = 0.730), but these remained below the required threshold.

For organizational performance enhancement (ACOE), however, two combined conditions exceeded the threshold. The configuration ACPDAC + ACDDDM recorded a consistency of

0.830, while ACPDAC + ACOAC achieved a consistency of 0.832. This indicates that the simultaneous presence of predictive data analytics capability with either data-driven decision-making or organizational analytics culture constituted necessary conditions for high organizational performance enhancement.

A further analysis of the necessary conditional effects revealed that all effect sizes were substantially below the 0.10 threshold commonly interpreted as a meaningful necessary effect. Although analytics infrastructure (ACAIN) and predictive modelling capability (ACPMC) produced statistically significant effects, their magnitudes remained very small (CR-FDH = 0.019 and 0.013 respectively) (Table 23). Therefore, none of the conditions can be regarded as individually necessary for achieving high financial forecasting accuracy.

Table 23. NCA Effect Sizes for Financial Forecasting Accuracy (ACFFA)

Condition	CE-FDH Effect Size	p-value	CR-FDH Effect Size	p-value	Interpretation
ACDQA	0.005	0.100	0.013	0.005	Small
ACAIN	0.011	0.012	0.019	0.000	Small
ACASE	0.006	0.102	0.008	0.040	Small
ACPMC	0.013	0.000	0.013	0.004	Small

For the NCA results shown in Table 24 analytics infrastructure (ACAIN) generated the largest effect size for risk management effectiveness (CR-FDH = 0.027). Nevertheless, the effect remained well below the minimum threshold for a practically relevant necessary condition. Data quality and accessibility, analytical skills and expertise, and predictive modelling capability demonstrated negligible effects.

Table 24. NCA Effect Sizes for Risk Management Effectiveness (ACRME)

Condition	CE-FDH Effect Size	p-value	CR-FDH Effect Size	p-value	Interpretation
ACDQA	0.005	0.063	0.004	0.061	Negligible
ACAIN	0.016	0.002	0.027	0.002	Small

Condition	CE-FDH Effect Size	p-value	CR-FDH Effect Size	p-value	Interpretation
ACASE	0.000	0.512	0.000	0.497	None
ACPMC	0.003	0.119	0.002	0.148	Negligible

Moreover, neither analytics infrastructure nor predictive modelling capability exhibited substantial necessity effects for operational efficiency (Table 25). Although both variables were statistically significant under the CE-FDH criterion, their effect sizes remained very small, indicating that operational efficiency can be achieved through multiple alternative paths rather than relying on any single necessary condition.

Table 25. NCA Effect Size for Operational Efficiency (ACOEF)

Condition	CE-FDH Effect Size	p-value	CR-FDH Effect Size	p-value	Interpretation
ACDQA	0.005	0.188	0.002	0.261	Negligible
ACAIN	0.012	0.022	0.008	0.052	Small
ACPMC	0.011	0.019	0.008	0.042	Small

Finally, predictive data analytics capability (ACPDAC) and data-driven decision-making (ACDDDM) exhibited statistically significant necessity effects; however, the effect sizes remained small. Organizational analytics culture (ACOAC) recorded zero effect sizes under both CE-FDH and CR-FDH methods, indicating that it was not a necessary condition for high organizational performance enhancement when considered independently (Table 26).

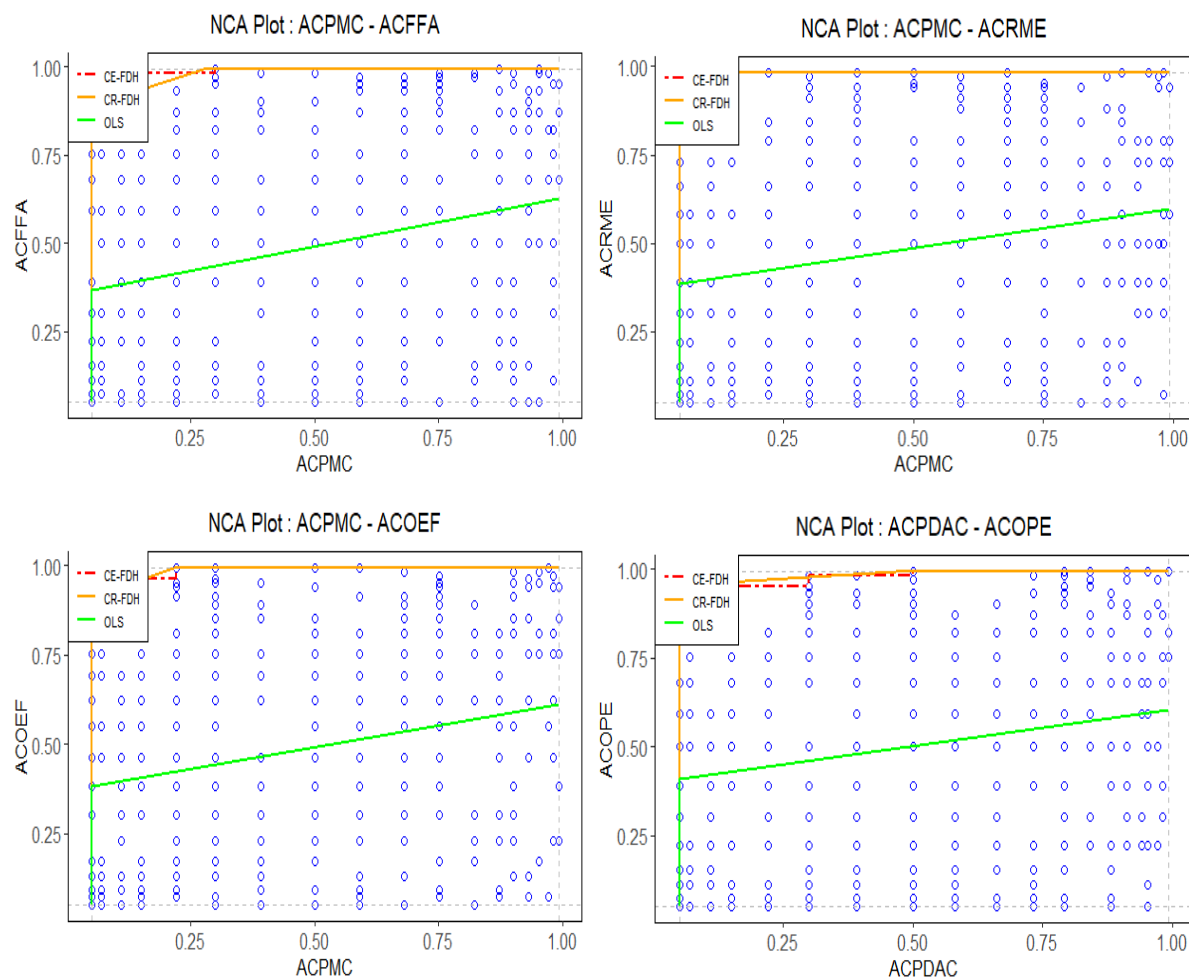
Table 26. NCA Effect Size for Organizational Performance Enhancement (ACOPE)

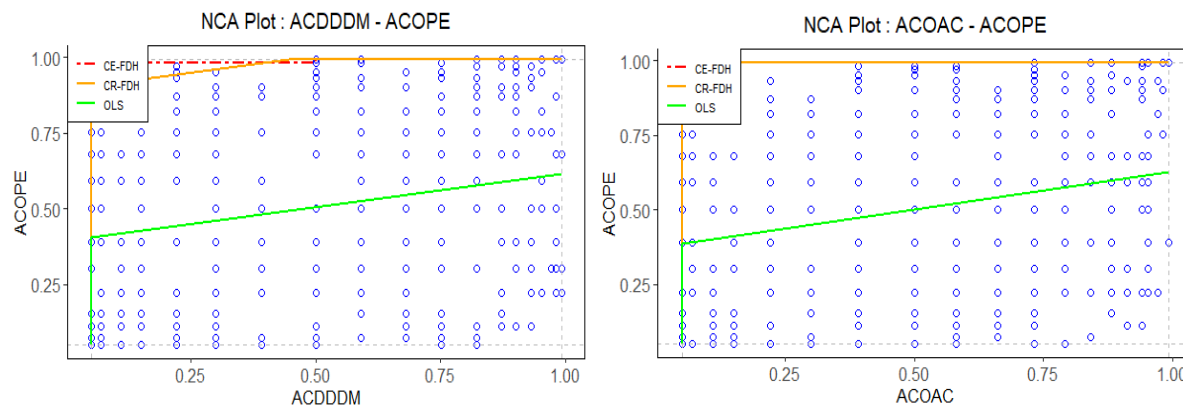
Condition	CE-FDH Effect Size	p-value	CR-FDH Effect Size	p-value	Interpretation
ACPDAC	0.014	0.002	0.009	0.005	Small
ACDDDM	0.015	0.000	0.019	0.000	Small

Condition	CE-FDH Effect Size	p-value	CR-FDH Effect Size	p-value	Interpretation
ACOAC	0.000	0.471	0.000	0.462	None

For better graphical the ceiling line plots shown in Figure 3 demonstrates the absence of large empty spaces in the upper-left corner of the scatterplot. This pattern indicates that none of the examined conditions imposed strong constraints on the achievement of high outcome levels. The limited ceiling zones observed are consistent with the very small effect sizes reported in Tables 22 to 26. Consequently, the NCA findings suggest that no individual condition constituted a strong bottleneck for organizational performance outcomes.

Figure 3. NCA Ceiling Line Plots





4.13 Sufficiency Condition Analysis (Truth Table)

Following the necessary condition analysis, a sufficiency condition analysis was conducted using fsQCA truth tables to identify combinations of conditions sufficient for achieving high levels of Financial Forecasting Accuracy (ACFFA), Risk Management Effectiveness (ACRME), Operational Efficiency (ACOF), and Organizational Performance Enhancement (ACOPE). Consistent with fsQCA conventions, the Quine-McCluskey minimization algorithm was applied. The analysis employed a frequency threshold of 13 cases for ACFFA, ACRME, and ACOF, and 30 cases for ACOPE. The consistency thresholds were 0.771, 0.775, 0.755, and 0.788 respectively, exceeding the minimum acceptable threshold of 0.75, thereby ensuring the reliability of the configurational solutions. Since the complex, parsimonious, and intermediate solutions produced identical results across all outcome variables, the intermediate solutions are reported and interpreted as the final configurational solutions. The sufficient configurations associated with high financial forecasting accuracy is presented in Table 27. The results indicate that no single predictive analytics capability dimension is solely responsible for achieving superior forecasting performance. Instead, multiple configurations of data quality and accessibility, analytics infrastructure, analytical skills and expertise, and predictive modelling capability jointly contribute to the outcome. Configuration F2 recorded the highest raw coverage (0.734), suggesting that the combination of strong data quality and accessibility, analytics infrastructure, and analytical skills explains the largest proportion of cases exhibiting high forecasting accuracy. In contrast, Configuration F4 produced the highest consistency score (0.700), indicating that when data quality and accessibility, analytical skills, and predictive modelling capability coexist, the likelihood of achieving high forecasting accuracy is greatest. The total solution coverage of 0.948 demonstrates that the identified configurations explain approximately 94.8% of membership in the high financial forecasting accuracy set. Although the solution consistency of 0.597 falls below the conventional threshold of 0.80 for strong sufficiency, it still suggests meaningful configurational relationships among the predictive analytics capability dimensions. These findings support the notion of equifinality, whereby several alternative combinations of predictive analytics resources can lead to comparable forecasting outcomes.

Table 27. Intermediate Configurations for Financial Forecasting Accuracy (ACFFA)

Configuration	ACDQA	ACAIN	ACASE	ACPMC	Raw Coverage	Unique Coverage	Consistency
F1	●	●	●	●	0.697	0.025	0.690
F2	●	●	●	○	0.734	0.039	0.693
F3	●	●	○	●	0.712	0.038	0.683
F4	●	○	●	●	0.691	0.021	0.700

Solution Coverage = 0.948; Solution Consistency = 0.597; Note: (●) = presence of condition; (○) = absence of condition.

The truth table (Table 28) further shows that the configuration involving the simultaneous presence of all four capability dimensions (1,1,1,1) achieved the highest raw consistency of 0.878 and the highest PRI consistency of 0.718. This indicates that firms possessing strong capabilities across all predictive analytics dimensions are more likely to achieve superior forecasting accuracy. Nevertheless, several other configurations also exceeded the consistency threshold, confirming that forecasting accuracy can be attained through multiple pathways rather than a single dominant route.

Table 28. Truth Table for Financial Forecasting Accuracy (ACFFA)

ACDQA	ACAIN	ACASE	ACPMC	Cases	Outcome	Raw Consistency	PRI Consistency
1	1	1	1	62	1	0.878	0.718
0	1	1	1	25	1	0.861	0.587
1	1	0	1	25	1	0.836	0.536
1	1	1	0	28	1	0.833	0.515
1	1	0	0	19	1	0.826	0.452
0	1	0	1	20	1	0.825	0.488

ACDQA	ACAIN	ACASE	ACPMC	Cases	Outcome	Raw Consistency	PRI Consistency
0	1	1	0	22	1	0.825	0.447
1	0	0	1	13	1	0.824	0.423
1	0	1	1	32	1	0.824	0.501
0	0	1	1	16	1	0.813	0.435
1	0	1	0	23	1	0.792	0.380
1	0	0	0	13	1	0.788	0.329
0	0	1	0	23	1	0.779	0.376
0	0	0	1	19	1	0.773	0.317
0	1	0	0	24	1	0.771	0.375
0	0	0	0	36	0	0.661	0.220

In addition, it is also evident that several combinations of predictive analytics capability dimensions are sufficient for enhancing risk management effectiveness. Configuration R2 achieved the highest raw coverage (0.742), implying that firms possessing strong data quality, analytics infrastructure, and analytical expertise explain the largest share of successful risk management cases. Configuration R1, however, recorded the highest consistency value (0.700), indicating that the simultaneous presence of all four capability dimensions provides the most reliable pathway toward effective risk management. The overall solution coverage of 0.944 suggests that the identified configurations account for approximately 94.4% of the observed outcome (Table 29). The solution consistency of 0.591 indicates moderate sufficiency. Collectively, the results imply that effective risk management is not dependent on a single predictive analytics capability but rather emerges from the interaction of multiple complementary resources.

Table 29. Intermediate Configurations for Risk Management Effectiveness (ACRME)

Configuration	ACDQA	ACAIN	ACASE	ACPMC	Raw Coverage	Unique Coverage	Consistency
R1	●	●	●	●	0.711	0.017	0.700
R2	●	●	●	○	0.742	0.039	0.696
R3	●	●	○	●	0.724	0.031	0.691
R4	●	○	●	●	0.688	0.020	0.692

Solution Coverage = 0.944; Solution Consistency = 0.591; Note: (●) = presence of condition; (○) = absence of condition.

The related truth table results (Table 30) reveal that the configuration comprising all four capability dimensions generated a raw consistency of 0.876 and PRI consistency of 0.685. Similarly, the configuration combining data quality, analytics infrastructure, and analytical expertise achieved the highest raw consistency (0.878). These findings suggest that analytical expertise and infrastructure play particularly important roles in translating predictive analytics capabilities into effective risk management outcomes.

Table 30. Truth Table for Risk Management Effectiveness (ACRME)

ACDQA	ACAIN	ACASE	ACPMC	Cases	Outcome	Raw Consistency	PRI Consistency
1	1	1	0	28	1	0.878	0.626
1	1	1	1	62	1	0.876	0.685
0	1	1	1	25	1	0.871	0.577
1	0	1	1	32	1	0.866	0.540
0	0	1	1	16	1	0.857	0.469
1	1	0	1	25	1	0.853	0.561

ACDQA	ACAIN	ACASE	ACPMC	Cases	Outcome	Raw Consistency	PRI Consistency
0	0	0	0	36	0	0.668	0.244

Moreover, operational efficiency is likewise driven by alternative combinations of predictive analytics capability dimensions (Table 31). Configuration O2 achieved the highest raw coverage (0.730), whereas Configuration O1 recorded the highest consistency score (0.704). This suggests that operational efficiency is most reliably achieved when all predictive analytics capability dimensions operate simultaneously. The solution coverage value of 0.946 indicates that the identified configurations collectively explain almost 95% of membership in the operational efficiency outcome set. Although the solution consistency remains moderate (0.597), the findings provide strong evidence that operational efficiency results from the synergistic interaction among analytics infrastructure, data quality, analytical expertise, and predictive modelling capability.

Table 31. Intermediate Configurations for Operational Efficiency (ACOEF)

Configuration	ACDQA	ACAIN	ACASE	ACPMC	Raw Coverage	Unique Coverage	Consistency
O1	●	●	●	●	0.709	0.020	0.704
O2	●	●	●	○	0.730	0.028	0.690
O3	●	●	○	●	0.721	0.038	0.693
O4	●	○	●	●	0.688	0.019	0.698

Solution Coverage = 0.946; Solution Consistency = 0.597; Note: (●) = presence of condition; (○) = absence of condition.

The associated truth table results (Table 32) demonstrate that the configuration involving data quality, analytics infrastructure, and analytical expertise achieved the highest raw consistency value (0.875). However, the full-capability configuration (1,1,1,1) also exhibited a strong consistency value of 0.852 and the largest number of cases ($n = 62$). This reinforces the argument that organizations derive greater operational benefits when predictive analytics capabilities are developed in a holistic manner.

Table 32. Truth Table for Operational Efficiency (ACOE)

ACDQA	ACAIN	ACASE	ACPMC	Cases	Outcome	Raw Consistency	PRI Consistency
1	1	1	0	28	1	0.875	0.643
0	1	1	1	25	1	0.864	0.573
1	1	0	1	25	1	0.852	0.570
1	1	1	1	62	1	0.852	0.660
0	0	0	0	36	0	0.669	0.225

Furthermore, the results identify several configurational pathways leading to organizational performance enhancement. The results reveal that predictive data analytics capability, data-driven decision-making, and organizational analytics culture combine in different ways to produce high organizational performance. Configuration P3 recorded both the highest raw coverage (0.709) and highest consistency (0.707), indicating that the combination of predictive data analytics capability and a strong analytics culture constitute the most reliable pathway to performance enhancement. Configuration P2 also demonstrated strong explanatory power, highlighting the importance of data-driven decision-making when combined with predictive analytics capability. The total solution coverage of 0.894 suggests that approximately 89.4% of the outcome is explained by the identified configurations, while the solution consistency of 0.640 indicates a moderate level of sufficiency (Table 33). These findings provide evidence that organizational performance enhancement can emerge through different combinations of technological capability, managerial decision-making orientation, and organizational culture.

Table 33. Intermediate Configurations for Organizational Performance Enhancement (ACOPE)

Configuration	ACPDAC	ACDDDM	ACOAC	Raw Coverage	Unique Coverage	Consistency
P1	●	●	●	0.697	0.044	0.695
P2	●	●	○	0.692	0.061	0.703

Configuration	ACPDAC	ACDDDM	ACOAC	Raw Coverage	Unique Coverage	Consistency
P3	●	○	●	0.709	0.063	0.707

Solution Coverage = 0.894; Solution Consistency = 0.640; Note: (●) = presence of condition; (○) = absence of condition.

The truth table (Table 34) further shows that the configuration consisting of data-driven decision-making and organizational analytics culture in the absence of strong predictive analytics capability (0,1,1) achieved the highest raw consistency (0.842). However, the configuration involving the simultaneous presence of predictive analytics capability, data-driven decision-making, and organizational analytics culture (1,1,1) represented the largest number of cases (n = 103) and maintained a high consistency level of 0.820. This demonstrates that organizational performance enhancement can be achieved through several equally effective pathways, thereby providing strong support for the principle of equifinality and complementing the findings obtained from the PLS-SEM analysis.

Table 34. Truth Table for Organizational Performance Enhancement (ACOPE)

ACPDAC	ACDDDM	ACOAC	Cases	Outcome	Raw Consistency	PRI Consistency
0	1	1	39	1	0.842	0.588
1	1	0	42	1	0.832	0.555
1	0	1	53	1	0.820	0.546
1	1	1	103	1	0.820	0.630
0	1	0	36	1	0.803	0.496
0	0	1	33	1	0.795	0.473
1	0	0	30	1	0.788	0.436
0	0	0	64	0	0.673	0.326

5. Discussion

The first objective of the study was to determine the usage levels, impact and primary use cases of predictive data analytics among SMEs in the FMCG sector in the USA. The results indicate that predictive analytics is used across a broad spectrum of business applications, with product performance analysis (68.8%), financial planning and budgeting (67.0%), demand forecasting (66.8%) and inventory management (66.3%) coming out on top. Further evidence of this is the high levels of use of Excel Forecasting Tools (82.7%) and Power BI (74.2%). Moreover, effectiveness scores were always good, ranging from 4.00 to 4.05, with mean scores of 4.05 for market responsiveness and decision quality. The results confirm that predictive analytics is not just about prediction; it can also help with other operational and strategic tasks. The results align with Ahmed et al. (2025), who determined that predictive analytics boosts agility, financial outcomes, risk management, and decision-making, and Riipa et al. (2025), who discovered that as analytics maturity rises, so do decision accuracy, cost efficiency, supply chain outcomes, and profitability. The findings on forecasting and planning are also strong in agreement with Uddin (2025) and Majumder (2025) while the findings regarding the application in the operation are in general consensus with Zainal and Faiz (2025) and Fallahieh et al. (2025). The current findings indicate a higher level of effectiveness of implementation, however, than the constraints reported by the study of Ahmed et al. (2025), Eyinade et al. (2025), and Zainal and Faiz (2025), which include data quality, skills, legacy systems, governance, and integration. This could be due to the relatively high adoption rates of the SMEs studied, with many getting beyond the stage of initial experimentation and into more advanced adoption.

Therefore, it is concluded that the research question of “Is predictive analytics broadly and effectively adopted by U.S. FMCG SMEs, and what are the perceived benefits of predictive analytics adoption in such SMEs for product, financial, forecasting, and inventory related activities?” is answered by the fact that predictive analytics is effectively and widely used among U.S. FMCG SMEs, especially for product, financial, forecasting and inventory related activities with perceived benefits of increased decision quality, market responsiveness, planning and operational performance.

The second research objective aimed to determine the impact of predictive data analytics capability on financial forecasting accuracy, risk management effectiveness and operational efficiency among FMCG SMEs in the United States. The PLS-SEM results demonstrate that the four dimensions of predictive data analytics capability had positive and statistically significant effects on all three outcomes. Data quality and accessibility and predictive modelling capability were particularly influential in financial forecasting accuracy, while analytics infrastructure and analytical skills and expertise were important for risk management effectiveness. Analytical skills and expertise and predictive modelling capability were the strongest predictors of operational efficiency. Consequently, all 12 hypotheses were supported.

The complementary fsQCA findings provide a configurational explanation of these relationships. Contrarian cases showed that some firms with relatively low analytics capabilities achieved high outcomes, while others with high capabilities recorded comparatively low outcomes. Moreover, none of the individual capability dimensions met the required consistency threshold to constitute a necessary condition for financial forecasting accuracy, risk management effectiveness or operational efficiency. This indicates that no single capability is indispensable and that SMEs may achieve similar outcomes through different combinations of capabilities.

The sufficiency analysis reinforces this interpretation. For financial forecasting accuracy, several configurations involving data quality and accessibility, analytics infrastructure, analytical skills and expertise, and predictive modelling capability were associated with high outcomes. The full combination of the four capabilities was particularly prominent, achieving a truth-table consistency of 0.878 across 62 cases. Similar patterns emerged for risk management, where combinations of data quality, infrastructure and analytical expertise produced high effectiveness, while the full-capability configuration achieved a consistency of 0.876. For operational efficiency, the combination of data quality, analytics infrastructure and analytical expertise recorded the highest consistency (0.875), while the full-capability configuration covered the largest number of cases and achieved a consistency of 0.852. The high solution coverage values for forecasting accuracy (0.948), risk management effectiveness (0.944) and operational efficiency (0.946) further demonstrate that the identified configurations explain a substantial proportion of high-outcome cases.

These findings suggest that predictive analytics capability operates through complementary combinations rather than through a single universally dominant capability. The PLS-SEM results demonstrate the significance of individual capabilities, whereas fsQCA shows that firms can combine these capabilities in different ways to achieve comparable outcomes, supporting the principle of equifinality. This is consistent with Uddin (2025) and Majumder (2025) regarding forecasting and financial outcomes, Chowdhury and Alvee (2025), Fallahieh et al. (2025) and Diameh et al. (2025) regarding risk management, and Zainal and Faiz (2025) and Riipa et al. (2025) regarding operational efficiency. The configurational findings may also explain why the constraints identified by Eyinade et al. (2025) and Zainal and Faiz (2025) do not uniformly prevent positive outcomes in the present study, as weaknesses in one capability may be offset by strengths in others. In essence, predictive data analytics capability significantly enhances financial forecasting accuracy, risk management effectiveness and operational efficiency, while the complementary fsQCA evidence demonstrates that these outcomes can be achieved through multiple combinations of analytics capabilities.

The third research objective sought to determine the mediating role of data-driven decision-making and the moderating role of organizational analytics culture in the relationship between predictive data analytics capability and organizational performance enhancement among SMEs in the FMCG

industry in the United States. The results indicate that the relationship between PDAC and OPE is significantly mediated by DDDM. This suggests that stronger predictive analytics capability contributes to improved organizational performance partly because it enables SMEs to make more informed, evidence-based decisions. The indirect effect is therefore important, while the direct effect of PDAC on OPE was not statistically significant. This indicates that the organizational benefits of predictive analytics may depend substantially on how analytical information is translated into managerial decisions. Hence, H13 is accepted.

The complementary configurational findings provide further insight into this relationship. The contrarian analysis identified firms in which relatively low predictive analytics capability coexisted with high organizational performance, as well as firms with relatively high capability but low performance. This finding is particularly relevant to the mediation result because it suggests that predictive analytics capability alone does not automatically translate into superior organizational performance. Rather, the organizational context in which analytics is combined with decision-making practices and other organizational conditions appears to matter.

The configurational analysis of organizational performance enhancement identified three pathways involving predictive data analytics capability, data-driven decision-making and organizational analytics culture. The combination of PDAC, DDDM and OAC recorded a high consistency of 0.820 and represented the largest number of cases ($n = 103$) among the configurations. At the same time, the configuration involving DDDM and OAC in the absence of strong PDAC recorded the highest raw consistency (0.842). This is particularly important because it demonstrates that high organizational performance does not necessarily require strong predictive analytics capability when effective data-driven decision-making and an analytics-oriented organizational culture are present. Conversely, predictive analytics capability can contribute to performance when it is embedded within appropriate decision-making and cultural conditions.

The solution coverage of 0.894 indicates that the identified configurations capture a substantial proportion of membership in the high organizational performance set. However, the solution consistency of 0.640 indicates that the configurations should not be interpreted as universally sufficient conditions. Rather, they provide evidence of alternative pathways through which organizational performance enhancement may occur. The results therefore reinforce the principle of equifinality and provide a more nuanced explanation of the non-significant direct PDAC – OPE relationship observed in the PLS-SEM analysis. In particular, they suggest that predictive analytics is more likely to generate organizational-level benefits when it is translated into decision-making practices and supported by an analytics-oriented organizational environment.

This discovery aligns with Sagar and Sagar (2026), which highlighted that data-driven decision-making enhances organizational resilience by enabling quicker responses and adaptive ability. It also aligns with Fallahieh et al. (2025) and Diameh et al. (2025), which indicate that analytics becomes more consequential when embedded within organizational decision processes. The

present findings extend these studies by showing that the relationship between analytics capability and organizational performance is not simply a direct technological relationship; it can emerge through decision-making mechanisms and different combinations of organizational conditions.

The moderating effect of OAC, however, was not supported. There was a positive but insignificant interaction between OAC and PDAC, and therefore H14 was rejected. This initially appears inconsistent with the configurational finding that OAC participates in pathways associated with high organizational performance. However, the two findings address different aspects of the relationship. PLS-SEM tests whether OAC changes the strength of the PDAC – OPE relationship, whereas fsQCA examines whether OAC forms part of a combination of conditions associated with high OPE. The configurational results show that OAC can contribute to performance when combined with PDAC and/or DDDM, without necessarily strengthening the statistical relationship between PDAC and OPE across the entire sample.

This distinction helps reconcile the present finding with studies by Ahmed et al. (2025), Chowdhury and Alvee (2025), Riipa et al. (2025) and Majumder (2025), which emphasize the importance of supportive organizational conditions for analytics outcomes. In the present study, OAC itself had a significant positive effect on OPE, while its interaction with PDAC was insignificant. The evidence therefore suggests that organizational analytics culture may function more effectively as a direct organizational resource or as part of a broader configuration of conditions than as a moderator that systematically changes the effect of predictive analytics capability on performance.

In all, the findings indicate that organizational performance enhancement among U.S. FMCG SMEs is better understood as the result of an interconnected system of analytics capability, decision-making and organizational conditions rather than as the consequence of predictive analytics capability operating independently. The PLS-SEM results establish the mediating role of data-driven decision-making and the direct contribution of organizational analytics culture, while the configurational analysis demonstrates that different combinations of these conditions can produce high organizational performance. This provides a more comprehensive explanation of how predictive analytics translates into organizational value and strengthens the conclusion that the organizational use of analytics, rather than analytics capability alone, is central to performance enhancement.

6. Conclusion

This study explored the adoption and productivity benefits of predictive data analytics for organizational performance improvement for SMEs in the FMCG sector in the USA. The results reveal that predictive analytics is no longer a mere technological tool but is now an essential strategic asset to assist forecasting, planning, risk management, inventory optimization and operational decision-making. The findings showed that predictive analytics is prevalent in FMCG

SMEs; organizations are using a large number of forecasting tools, business intelligence applications and data-driven planning systems in multiple business functions.

The study more broadly confirmed that predictive data analytics capability; in particular, data quality and accessibility, analytics infrastructure, analytical skills and expertise, and predictive modelling capability, has a significant impact on the accuracy of financial forecasting, effectiveness of risk management and efficiency of operations. The results indicate that analytics capabilities are valuable organizational resources which improve the quality of business decisions and organizational responsiveness in dynamic markets. In addition to the direct relationship between capability and performance, the study found that there is a critical mediation by data-driven decision making between the two. This result suggests that the benefit of predictive analytics is only realized when analytics becomes useful for business decisions and actions. While organizational analytics culture had no significant moderating effect on the PDAC–performance relationship, it did have a direct positive effect on organizational performance and was a key determinant in the high-performance organizational configurations identified using the fsQCA. The results of the combined PLS-SEM and fsQCA analysis indicate that the organizational performance-enhancing capabilities are interconnected, linking analytics capabilities to decision-making processes and supportive organizational conditions. Thus, technology investments alone are not going to bring sustainable performance gains for FMCG SMEs. Rather, organisations need to build data quality, analytical capabilities and predictive modelling skills, data-driven decision processes, and analytics cultures all at the same time. The proposed Predictive Data Analytics – Enhanced Performance Framework (PDA-EPF) then offers a viable approach to turning predictive data analytics into a smart decision support capability that creates ongoing value and competitive advantage for organizations.

6.1 Implications and General Recommendations

The results of this study hold critical theoretical and practical significance for predictive analytics research, as well as the management and policy aspects of adopting predictive analytics by SMEs.

6.1.1 Theoretical Implications

From a theoretical perspective, the study advances both Dynamic Capabilities Theory (DCT) and Organizational Information Processing Theory (OIPT). The results show that predictive data analytics is a strategic dynamic capability that can help organizations sense, process, and act quickly to market uncertainty. Empirical findings of the significant impacts of the four capabilities of data quality & accessibility, analytics infrastructure, analytical skills & expertise, and predictive modelling capability on organizational outcomes support the proposition that organizational performance can be created through the coordinated deployment of complementary capabilities as opposed to capabilities as stand-alone technological resources. The study has also advanced OIPT by establishing that not just information-processing capacity but also the capacity of the organization to transform processed information into actionable decisions has an impact on

organizational performance. The significance of the mediating role of data-driven decision-making highlights the fact that the value of analytics capabilities is largely created when managerial decision-making is embedded in analytics. In addition, the results from the combined PLS-Sem and fsQCA analysis make a relevant contribution to the field of analytics literature by demonstrating that similar organizational (outcome) effects can be achieved with various capability configurations, which broadens the existing knowledge in the field of predictive analytics research on equifinality. The study also contributes to the current knowledge base in the area of analytics capability as it offers empirical evidence in the context of FMCG SMEs, which is still a relatively under-researched area in the field of predictive analytics.

6.1.2 Practical Implications and Recommendations

From a practical perspective, the results indicate that the SMEs should not be merely thinking of predictive analytics as a reporting or data collection tool, but as something that would be capable of making intelligent decisions. Investments should be made in data quality, analytics infrastructure, employee analytical ability and predictive modelling. Formal decision-making processes should be developed and remain in place to allow predictive information to be used in a systematic way to inform financial planning, inventory management, demand forecasting, risk assessment and operational strategy decisions. The proposed PDA-EPF also suggests the re-engineering of the existing enterprise tools by integrating Artificial Intelligence. The traditional ERP systems, CRM, Supply Chain Management systems, forecasting applications, and Business Intelligence tools should all become intelligent, with functions like automated data interpretation, anomaly detection, predictive forecasting, scenario simulations, recommendation generation, and contextual decision guidance. These systems should deliver real-time alerts, auto workflow execution and custom suggestions according to the current business scenario, not just descriptive reports. Policymakers and institutions that support SMEs should create initiatives to provide predictive analytics support to SMEs such as subsidies for accessing analytics platforms, cloud-based analytics infrastructure, AI-enabled business solutions, analytics capability training, and workforce development programs. There are also financial incentives and technical assistance programs that can help lower barriers to adoption for SMEs who may not have the resources to adopt advanced analytics technologies. They can boost the competitiveness, resilience, productivity, innovation capacity, and long-term sustainability of SMEs, and increase the overall impact of the FMCG sector on the economic growth and employment creation in the United States.

6.1.3 Predictive Data Analytics-Driven Enterprise Performance Framework (PDA-EPF) for FMCG SMEs in the United States

The proposed Predictive Data Analytics–Enhanced Performance Framework (PDA–EPF), demonstrates how FMCG SMEs in the United States can move predictive data analytics beyond its current status of data collection and reporting into an intelligent decision support and performance enhancement system (Figure 4). The framework has been shaped and informed by



the results of this study, existing literature and emerging trends in the field of AI, machine learning, business intelligence and enterprise analytics. The PDA–EPF does not simply focus on forecasting and reporting as the traditional predictive analytics systems did, but it is about the generation of intelligence in a continuous manner, automated decision support, executing workflow, learning from the organization and optimizing its performance.

The framework acknowledges that most SMEs have disjointed data systems, application systems that are not integrated and lack analytical capacities. As a result, valuable organizational data may not be used in a meaningful way even though they are created every day as a part of business activities. Thus, the PDA–EPF suggests an enterprise-wide ecosystem of intelligent analytical platforms that interoperably integrate internal and external data sources and provide meaningful recommendations, contextually driven decision-making and continuous organizational performance improvement.

The first layer of the framework is the external intelligence and environmental scanning layer. This layer receives data from suppliers, logistics partners, channel and distribution partners, customers, regulators, investors, technology vendors, cloud service providers and more. It also keeps track of macroeconomic conditions, inflation trends, seasonal variations, competitor activities, regulatory changes, consumer sentiments, and market dynamics. The suggested framework does not just involve passive monitoring but proposes to integrate AI-driven signal detection systems that can automatically detect new opportunities, threats, disruptions, and market changes. These would facilitate the shift of SMEs from reactive to proactive and anticipatory decision-making.

The second part is about integration and ecosystem connections in real-time. The framework suggests that enterprise resource planning (ERP), customer relationship management (CRM), point-of-sale (POS), e-commerce, loyalty programs, supply chain databases, social media and the Internet of Things (IoT) sensors be linked to a single data environment. Existing systems need to be reengineered via API connectivity and cloud-based integration architectures to enable seamless data flows between functional departments. The integration allows decision makers to see an overall organizational picture and not just their departmental picture.

After the data integration, an AI-powered data quality and governance layer is added as part of the framework. The issue of data quality is one of the biggest challenges for SMEs to achieve success with predictive analytics. So, the framework suggests integrating intelligent data cleansing, anomaly detection, standardization, validation and harmonisation features into the information systems of organisations. Machine learning algorithms can be used to automatically identify missing data, duplicate records, unusual transactions, inaccurate predictions, and reporting inconsistencies. At the same time, data governance policies should promote privacy, security, compliance and ethical data usage.

At the core of the PDA–EPF is the reengineered predictive analytics and AI engine. This module evolves a traditional predictive analytics system into a full-fledged decision intelligence system.

The system is not designed to forecast future trends and scenarios, but is constantly analyzing historical, current and stream data to provide business insights, establish causal relationships, simulate alternative scenarios and suggest best courses of action. Advanced analytical features like machine learning, deep learning, AutoML, generative AI, optimisation algorithms and prescriptive analytics should be built into current analytical tools. Therefore, when SMEs ask about what is likely to happen, they can also get answers on why it may happen, what should be done, and what is likely to happen, under various situations.

The framework also recommends the development of an intelligent decision support platform. The classic dashboard gives managers descriptive reporting which leaves them to make their own interpretation of the information before taking action. In the PDA–EPF, dashboards transform into a smart advisory system that can produce natural language explanations, visual storytelling, exception alerts, and scenario-based guidance, in addition to providing automated recommendations. If sales projections suggest that demand is falling, for instance, the system should automatically suggest inventory cuts, marketing strategy changes, price changes, or discussions with suppliers, based on past trends and market conditions. This will have a dramatic impact on decision making speed and enhance manager confidence and uniformity.

The Artificial Intelligence (AI) based decision guidance and response automation system is a unique feature of the PDA–EPF. The framework aims at incorporating rule-based intelligence and machine learning models into the operational processes to activate pre-defined responses in specific situations. For example, when demand spikes, inventory reordering suggestions, production capacity adjustments, or logistics adjustments can be automatically implemented. Likewise, a disruption in the supply chain can trigger supplier diversification, safety stocks and other distribution strategies. This way, predictive analytics becomes more of a decision partner than a report tool.

The framework also gives birth to an artificial intelligence-driven layer of workflow execution and operational response. This layer allows predictive insights to be converted to actual, real-time operations. Intelligent automation can help with inventory management, pricing decisions, promotional planning and management, logistics optimization, customer engagement, supplier collaboration, and resource allocation. Workflow automation can minimize manual tasks involved in routine decision making and free up time for managers to work on strategic tasks.

Being aware of the constantly changing nature of business environments, the PDA – EPF has a continuous learning and feedback system. All decision outcomes are learning opportunities for the system. Performance is monitored regularly and is fed back into the analytical models for re-calibration and improvements. As new data becomes available within the organization, machine learning algorithms adapt and learn, making accurate predictions relevant over time. This continuous cycle of improvement improves forecast accuracy, improves risk management and boosts operational efficiency.



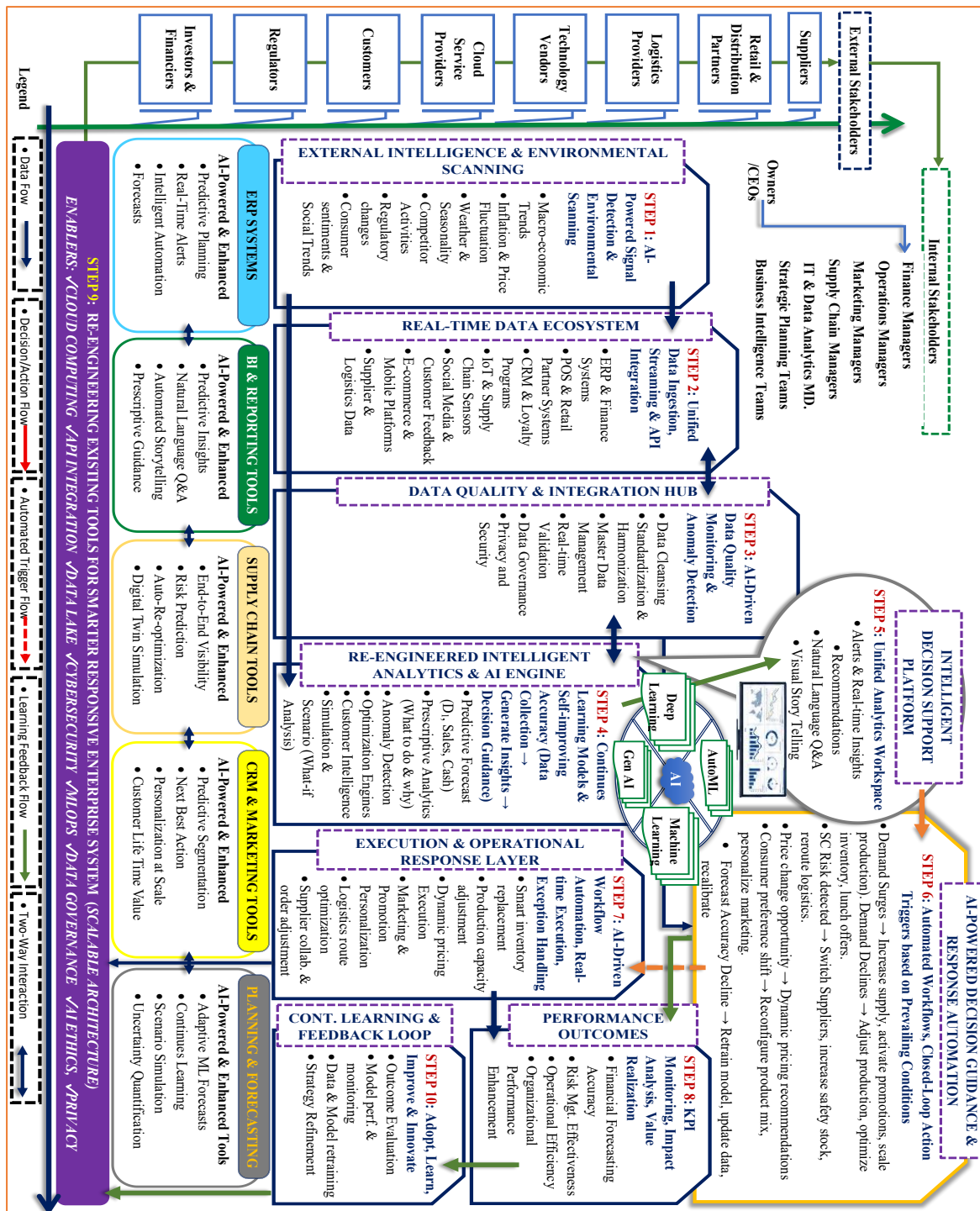
The framework suggests reengineering of the enterprise tools which are widely used in the FMCG SMEs to support implementation. ERP systems need to become more than just transaction processors; they should be AI-driven systems that can provide predictive forecasting, automated alerts, and planning suggestions. BI and reporting capabilities should include capabilities for natural language query, automated insight generation and prescriptive analysis. A supply chain management system should incorporate risk prediction, digital twin simulation and autonomous optimization functions. Predictive segmentation, next-best-action suggestions, customer lifetime value analysis, and customized engagement methods are key features in CRM/marketing platforms. Likewise, planning and forecasting should be based on adaptive machine learning models, uncertainty quantification methods, and scenarios simulation capabilities that enhance the effectiveness of planning.

Several enabling technologies and organizational capabilities are needed for the successful implementation of the PDA–EPF. These involve cloud computing infrastructure, API-driven integration designs, enterprise data lakes, robust data governance policies, mechanisms for protecting privacy, cybersecurity frameworks, guidelines for AI ethics, and MLOps capabilities. In addition, organizations need to build analytical skills and create a culture of data usage, and promote cross-departmental collaboration between business managers and analysts.

In conclusion, the PDA–EPF is a tool that can be used strategically by FMCG SMEs to harness predictive data analytics to enhance sustainable performance. The framework illustrates the progression of predictive analytics from the forecaster to a fully-fledged business intelligence tool that can aid financial forecasting accuracy, risk management effectiveness, operational efficiency, and overall organizational performance enhancement. Through the ability to combine AI-driven analytics, automated decision support, workflow automation and the ability to constantly learn, FMCG SMEs can increase their agility in reacting to market conditions, enhance their competitive edge and build long-term organizational resilience in the ever-changing business landscape.



Figure 4. Proposed Predictive Data Analytics-Driven Enterprise Performance Framework for FMCG SMEs in the United States



6.2 Limitation and Further Research Directions

The study was cross-sectional, with a main reliance on self-reported perceptions of FMCG SME decision makers at one time point. As a result, the causal relationship and the impact of predictive analytics use over time has not been fully proven and conclusions may be constrained by the individual perceptions of respondents and by context. On this note, further research is needed in other sectors, other countries and SME sub-segments, to see if the correlations found are consistent in other institutional and economic settings. The impact of the analytics capabilities on a firm's financial and operational performance over time should also be assessed in longitudinal studies, rather than on initial cross-sectional perceptions. Other factors that may influence the impact of analytics on performance, such as managerial capability, innovation capability, organizational learning, digital transformation maturity, AI integration and strategic agility; just to name a few, and the reasons why organizational analytics culture has a direct impact on performance without having a significant moderating effect on the relationship between predictive data analytics capability and organizational performance enhancement. The proposed PDA-EPF should be further tested and adapted in various industries and organizational settings to evaluate its generalizability and feasibility as a practical model to implement.

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Appendix 'A': Research Instrument

Introduction

This questionnaire seeks to collect information on the use of predictive data analytics and its contribution to organizational performance among SMEs in the FMCG industry in the United States. Your responses will be treated with strict confidentiality and will be used solely for academic research purposes. There are no right or wrong answers; kindly provide responses that best reflect your organization's current situation.

Section A: Socio-Demographic Characteristics of Respondents

Please tick (✓) the option that best describes you.

A1. Gender

☐ Male

☐ Female

A2. Age Group

☐ Below 25 years

☐ 25–34 years

☐ 35–44 years

☐ 45–54 years

☐ 55 years and above

A3. Highest Educational Qualification

☐ High School Diploma

☐ Associate Degree

☐ Bachelor's Degree

☐ Master's Degree

☐ Doctorate Degree

☐ Other (Specify) _____

A4. Current Position in the Organization

☐ Owner/Founder

☐ Chief Executive Officer

☐ Managing Director

☐ Finance Manager

☐ Operations Manager

☐ Supply Chain Manager

☐ IT/Data Analytics Manager

☐ Business Intelligence Manager

☐ Other (Specify) _____

A5. Number of Years Worked in the Organization

☐ Less than 1 year

☐ 1–3 years

☐ 4–6 years

☐ 7–10 years

☐ More than 10 years

A6. Firm Size (Number of Employees)

☐ Less than 50

☐ 50–99

☐ 100–249

☐ 250–499

☐ 500 and above

A7. Number of Years the Firm Has Been in Operation

☐ Less than 5 years

☐ 5–10 years

☐ 11–15 years

☐ 16–20 years

☐ More than 20 years

Section B: Extent, Effectiveness and Applications of Predictive Data Analytics

B1. Level of Predictive Data Analytics Adoption

How would you describe your organization's level of predictive analytics adoption?

☐ Not adopted

☐ Initial adoption

☐ Basic adoption

☐ Moderate adoption

☐ Advanced adoption

☐ Fully integrated across operations

B2. Frequency of Predictive Analytics Use

How often is predictive analytics used in your organization?

☐ Never

☐ Rarely

☐ Occasionally

☐ Monthly

☐ Weekly

☐ Daily

B3. Duration of Predictive Analytics Usage

☐ Less than 6 months

☐ 6 months – 1 year

☐ 1–2 years

☐ 2–5 years

☐ More than 5 years

B4. Areas Where Predictive Analytics Is Applied (*Select all that apply*)

☐ Sales forecasting

☐ Demand forecasting

☐ Inventory management

☐ Pricing decisions

☐ Customer analytics

☐ Supply chain management

☐ Risk assessment

☐ Marketing campaign planning

☐ Financial planning and budgeting

☐ Product performance analysis

☐ Other (Specify) _____

B5. Predictive Analytics Tools Used (*Select all that apply*)

☐ Microsoft Excel Forecasting Tools

☐ Power BI

☐ Tableau

☐ Python

☐ R

☐ IBM SPSS

☐ SAP Analytics

☐ Oracle Analytics

☐ Microsoft Azure AI

☐ AWS Analytics

☐ Google Cloud Analytics

☐ SAS Analytics

- ☐ Machine Learning Platforms
☐ Custom-Built Analytics Systems
☐ Other (Specify) _____

B6. Perceived Effectiveness of Predictive Analytics Implementation

Please indicate your level of agreement with the following statements.

Scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Code Statement

- PEI1 Predictive analytics has improved the quality of decisions in our organization.
PEI2 Predictive analytics has improved our ability to anticipate future business trends.
PEI3 The use of predictive analytics has improved operational planning in our organization.
PEI4 Predictive analytics has enhanced coordination across business functions.
PEI5 Predictive analytics has improved the accuracy of our business forecasts.
PEI6 Predictive analytics has helped reduce operational uncertainties.
PEI7 Predictive analytics has improved our response to changing market conditions.
PEI8 The benefits gained from predictive analytics outweigh the costs involved.
PEI9 Predictive analytics has contributed positively to overall business performance.
PEI10 Our organization has achieved measurable improvements from predictive analytics implementation.

Section C: Study Constructs

Response Scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Predictive Data Analytics Capability (PDAC) (Ahmed et al., 2025; Riipa et al., 2025)

Code Statement

- PDAC1 Our organization has strong capabilities for collecting, managing, and analyzing data for future planning.
PDAC2 Predictive analytics capabilities are well developed across our organization.
PDAC3 Our organization effectively uses predictive analytics to support business decisions.
PDAC4 We possess the necessary resources and competencies to implement predictive analytics successfully.
PDAC5 Predictive analytics has become an important capability within our organization.

Data Quality and Accessibility (DQA) (Eyinade et al., 2025; Ahmed et al., 2025)

Code Statement

- DQA1 Data needed for decision-making are readily available when required.
DQA2 Data used in our organization are generally accurate and reliable.

Code Statement

DQA3 Different departments have access to consistent data for analysis.

DQA4 Business data are updated regularly to support timely decisions.

DQA5 Employees can easily obtain the data needed for their work.

Analytics Infrastructure (AIN) (*Riipa et al., 2025; Celestin et al., 2025*)

Code Statement

AIN1 Our organization has adequate software tools for predictive analytics.

AIN2 We have reliable databases that support analytics activities.

AIN3 Our technology systems can process and analyze large volumes of data.

AIN4 Cloud-based analytics resources are available when needed.

AIN5 Our analytics infrastructure supports efficient decision-making.

Analytical Skills and Expertise (ASE) (*Celestin et al., 2025; Eyinade et al., 2025*)

Code Statement

ASE1 Employees possess the skills required to analyze business data.

ASE2 Staff can interpret analytics results effectively.

ASE3 Employees understand how predictive analytics supports business decisions.

ASE4 The organization provides opportunities to improve analytics skills.

ASE5 Our workforce has sufficient expertise to use predictive analytics tools effectively.

Predictive Modelling Capability (PMC) (*Uddin, 2025; Celestin et al., 2025*)

Code Statement

PMC1 Our organization uses predictive models to forecast future outcomes.

PMC2 Predictive models are regularly used to support planning activities.

PMC3 Predictive models help identify future business opportunities.

PMC4 Predictive models help anticipate potential business challenges.

PMC5 Predictive modelling contributes to better organizational decisions.

Data-Driven Decision-Making (DDDM) (*Sagar & Sagar, 2026; Fallahieh et al., 2025*)

Code Statement

DDDM1 Important decisions are based on data analysis rather than assumptions.

DDDM2 Managers regularly use analytics results when making decisions.

DDDM3 Business decisions are supported by evidence from organizational data.

DDDM4 Data insights are considered before major actions are taken.

DDDM5 Analytics findings play an important role in strategic planning.

Organizational Analytics Culture (OAC) (*Ahmed et al., 2025; Chowdhury and Alvee, 2025*)

Code Statement

- OAC1 Management encourages the use of analytics in decision-making.
- OAC2 Employees are encouraged to rely on data when solving problems.
- OAC3 The organization values evidence-based decision-making.
- OAC4 Departments actively share data and analytics knowledge.
- OAC5 The use of analytics is supported across different levels of the organization.

Organizational Performance Enhancement (OPE) (Riipa et al., 2025; Ahmed et al., 2025)

Code Statement

- OPE1 Our organization's overall performance has improved over the past few years.
- OPE2 Our organization consistently achieves its operational and business objectives.
- OPE3 We have experienced noticeable improvements in organizational effectiveness.
- OPE4 Our organization performs better today than it did before adopting advanced analytics practices.
- OPE5 Overall, our organization has achieved positive performance outcomes from its business operations.

Financial Forecasting Accuracy (FFA) (Uddin, 2025; Majumder, 2025)

Code Statement

- FFA1 Our financial forecasts closely match actual business outcomes.
- FFA2 We can accurately predict future sales trends.
- FFA3 Revenue forecasts have become more reliable over time.
- FFA4 Demand forecasts support effective financial planning.
- FFA5 Forecasting accuracy has improved in recent years.

Risk Management Effectiveness (RME) (Chowdhury and Alvee, 2025; Diameh et al., 2025)

Code Statement

- RME1 Potential business risks are identified early in our organization.
- RME2 Our organization effectively monitors operational and financial risks.
- RME3 Risk-related information supports timely management actions.
- RME4 The organization responds effectively to emerging risks.
- RME5 Our risk management processes reduce business disruptions.

Operational Efficiency (OEF) (Zainal & Faiz, 2025; Riipa et al., 2025)

Code Statement

- OEF1 Business processes are carried out efficiently in our organization.
- OEF2 Resources are utilized effectively to achieve organizational goals.



Code Statement

OEF3 Analytics has helped improve productivity across operations.

OEF4 Inventory and supply chain activities are managed efficiently.

OEF5 Our organization can respond quickly to operational challenges.

Thank You

Thank you for taking the time to complete this questionnaire.