

From Data to Decisions: A Data-Driven Management Framework for Enhancing Strategic Decision-Making Through Business Analytics

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Abstract: This research develops and evaluates a data-driven business analytics framework designed to enhance strategic decision-making within organizations. We examine how business analytics capabilities, big data utilization, predictive modeling, data visualization, and organizational analytics maturity collectively influence decision quality and overall performance. A quantitative cross-sectional design was employed, involving 200 organizations from manufacturing, finance, healthcare, retail, IT, and service sectors. Stratified random sampling yielded 1,000 respondents, including senior executives, analysts, and managers, with 972 valid responses retained after data cleaning. Primary data were collected through structured questionnaires and executive interviews, while secondary data came from organizational reports and industry databases. Statistical analyses included multiple linear regression, structural equation modeling, and confirmatory factor analysis. The results demonstrate that business analytics capability ($\beta = 0.47, p < 0.001$), data quality ($\beta = 0.41, p < 0.001$), predictive analytics ($\beta = 0.36, p < 0.001$), and data visualization ($\beta = 0.30, p = 0.002$) are significant predictors of strategic decision-making, with the model explaining 76.4% of the variance ($R^2 = 0.764$). Correlation analysis reveals a strong positive relationship between business analytics maturity and strategic decision-making effectiveness ($r = 0.84, p < 0.001$), as well as with organizational performance ($r = 0.80, p < 0.001$) and innovation capability ($r = 0.77, p < 0.001$). Structural equation modeling confirms good model fit (CFI = 0.98, RMSEA = 0.042). Organizations with advanced analytics capabilities outperform those with low maturity by 30.2% in strategic decision quality and 27.4% in operational efficiency. This study contributes a comprehensive, empirically validated framework that demonstrates analytics maturity as a critical enabler of evidence-based management and competitive advantage. The findings underscore the imperative for organizations to invest in analytics infrastructure, data governance, and workforce analytical skills to build data-driven enterprises.

Keywords: Business Analytics, Data-Driven Decision-Making, Strategic Management, Analytics Maturity, Organizational Performance

Introduction

Today's business climate presents leaders with today's challenge and opportunity: to manage more data in more situations at a more rapid pace, all by the name "a ton, Toni, and Tony. This raw data has evolved into one of the most significant indicators of success and continuity in the hotly competitive market today—converting it into strategic insight and action. Ontime calls for evidence-based decision-making models, which use advanced analytics, are replacing models based on common sense and intuition (Davenport & Harris, 2017). This has been referred to as a “paradigm shift” and is making business analytics a core component of business strategy and business plans and altering the way business and strategies are planned and implemented (Dietrich et al., 2014). The key thesis of this study is that the maturity of the organization in terms of business analytics (BA) levels (as manifested in the maturity of the business analytics infrastructure, analytical skills, and business analytics governance) is a major component of business analytics that significantly influences the organization's overall performance because it plays the critical part in making sound strategic decisions.

While all will attest that data driven management has numerous attractions, many organisations aren't realizing the benefits of their analytics investments. A frequent issue that is encountered is integrating the analytic value into the strategic planning process is not clearly defined (Loshin, 2012). Many reasons have been identified for this disconnect such as lack of data quality, lack of analytical talent, cultural resistance to data-driven changes, and the absence of one common framework, where the analytics capabilities and tools are linked to the strategic outcomes (Burk & Miner, 2020). While some components of this ecosystem have received attention to date, such as big data (Schmarzo, 2013) or the impact of predictive modelling on decision making in Africa (Adesina et al., 2024), a comprehensive synthesis bringing these together, and which forms the basis for a framework and models to support strategic decision making, does not exist and is in need of empirical testing.

The main aim of this research is to build and test an empirical model of how the maturity of business analytics affects the strategic decision making effectiveness and performance of the organization as a whole through a set of causal relationships. We also believe that higher analytics maturity will be correlated to the higher decision quality and that operational efficiency and innovation, competitive advantage are correlated to the analytics maturity, and that higher data governance are correlated to higher predictive capability and improved data visualization. To investigate this hypothesis, a quantitative research method, as well as a cross sectional research design, were used in order to obtain data from 200 organisations in some diverse industries including manufacturing, finance, health care, retail, information, technology and services (Ostrom et al., 2010). There were 1,000 senior executives, business analysts, data scientists and operations managers sampled to get a more complete cross-section of people's experience and understanding of analytics and analytics impact.

This research has three contributions. First, it provides a comprehensive, empirical-based list of features, including all aspects of business analytics (capability, data quality, predictive modeling and visualization) in one model to foresee strategic decision-making. Second, it provides compelling quantitative data from a relatively large sample including a diverse selection of companies, that helps build a picture of the large and sometimes quite stark differences between analytics maturity levels between organisations. Third—and most relevant to practitioners—specific investments can be planned and executed to improve the quality of data and the performance of the organization, from improvement of workforce skills to data governance, among others. The pertinent literature is summarized in the next section (Section 2), on business analytics, business strategic decision management, and organisation's maturity model. In section 3 the researchers describe the method of research conducted during this

research with the sampling techniques, instruments of data collection and data analytic techniques used. Empirical findings that have been discussed in section 4 encompass descriptive statistics, regression and structural equation modelling. The implications of these findings are presented in Section 5 – Theory and Practice and Section 6 presents the conclusions of the paper with contributions that are important and directions for future research.

Literature Review

This study is based on the following interrelated theories including Resource-based view (RBV) theory, Dynamic capabilities and information systems success models. As far as the RBV is concerned, the valuable, rare, inimitable, and non-substitutable resources possessed by an organization is the basis for the competitive advantages that it can obtain (Grant, 1991). In this context, business analytics capabilities are like a strategic asset that, if well-developed and wellapplied, will assist decision making or performance of the organization. This was further discussed by the scholars and they believe that as per the environment from where the data or analytical tools are being utilized, having those alone is not enough, but if they are equipped with the capacity to organize them to “integrate, create, and reconfigure” them, then they are useful for them (Eisenhardt & Martin, 2017). This lens is particularly helpful when interpreting the maturity of analytics over time, how analytics evolves to continue to provide strategic advantage and how it can be adapted as a consequence.

The correlation between business intelligence (BI) systems and productivity of decision making has been investigated in an extensive body of literature. The initial research in this area was on the technical lines of creating data warehousing and reporting systems, which revealed that with proper design, Business Intelligence (BI) systems enhanced the availability of information and decision making time (Chen et al., 2012). Subsequent research has been more interested in cultural and organizational factors that impact the impact of analytics on strategy. For instance according to the studies conducted, data quality and data governance are important conditions for the effective use of data and for deriving meaningful and useful insights: bad data equals bad analytical output equals decreased level of confidence in output and decreased trust and value in the resulting recommendations (Batini & Scannapieca, 2006). Similarly, data visualization is known to be an important tool in communicating complex analytic results to business leaders (Tufte & Graves-Morris, 1983), and responsive information-dashboards and visual analytics tools are recognized as helping business leaders identify patterns, trends and anomalies (Fisher & McCabe, 2006; Eave, 2015).

Another important aspect of business analytics maturity that has been the focus of much theoretical scholarship is predictive analytics. The use of statistical modeling, ML and forecasting methods enable companies to make informed predictions about future events and chisel out a risk analysis and make informed decisions for future plans (Siegel, 2013). Other studies, such as in areas of finance, healthcare, retail, etc., have revealed superior results with respect to a range of performance metrics for companies that use advanced predictive technology, such as for customer retention, supply chain optimisation, and fraud detection (Shmueli et al., 2016). However, the embedding of analysis insights in planning cycles and resource deployment decision-making requires changes in organization structures and processes that put the insights of analysis to work and turn them into action (Davenport et al., 2010).

Described Analytics Maturity in terms of a number of stage-based models, which demonstrated that descriptive reporting can progress to prescriptive optimisation. The framework of these models usually encompasses aspects of data management, analytical capabilities, organizational culture and governance (Grossman, 2018). Based on previous studies done using the same maturity models, companies who achieved higher maturity are outdoing those with lower maturity in multiple business

metrics, including customer satisfaction, market share and profit (Langer, 2025). However, most of this study has been descriptive in nature or conducted on a small-scale level of case study, a limitation of generalizability of its findings.

Some of the gaps in the former studies will be taken care of in the present study as follows. To start, while research has focused on each constituent element of the analytics-decision making relationship, there has been limited research that integrates the drivers of analytics capability, data quality, predictive modelling, and data visualization, and which has been tested empirically. Second, most of the empirical studies available at present are confined to a specific sector (or organisation) and are open to the question of external validity since the results of past studies cannot be generalized without further investigation. A large number of organizations (200) expressed involvement in our study, and the results are generalizable in many ways because we sought to capture a diverse sample of sectors. Third, the nomological network of the key constructs can be retested by using the help of the “structural equation modelling” that assesses the reliability of the theoretical model while the simpler analytical methods of the tests cannot. The current research subsequently offers a holistic data-driven management framework for practice on which it is verified that analytics maturity is crucial and enlightens how analytics maturity is linked to better organizational performance and decisions.

Methodology

Research Design and Sampling Strategy

This study was quantitative in nature and used a cross sectional research design that aimed for the development and testing of the data-driven business analytics solution for business solutions to aid in strategic decision making. The crosssectional approach was utilized because multiple variables were measured at only one time on a large sample enabling the various relationships between the Business Analytics Capabilities, Organizational Maturity, and the Business Outcomes to be examined at the same period. It serves 200 organizations across six different sectors, including manufacturing, finance, healthcare, retail, information technology and service. A multi-sectoral sampling strategy was conducted to attempt to strengthen the generalizability of findings and external validity of the study results from the single sector studies so far conducted (Ostrom et al., 2010).

Stratified random sampling by size of organization and industry sector and role of the respondent was used to select a random sample of 1,000 respondents. The respondent group spanned key players in the form of senior executives, business analysts, data scientists, operations managers and department heads, which meant that multiple stakeholders and viewpoints of analytics practices and their impact were captured from the respondents. This multiple-level sampling technique is the same as recommended in literature for organizational research in getting a complete picture of all organizational issues from informants at various levels (Ghauri et al., 2020). After cleaning the data, the number of valid responses that were received was: 972 (97.2% response rate), incomplete responses were filtered out using outlier detection method: Interquartile Range (IQR).

Data Collection Instruments and Variables

The data collected were of primary type, which had structured questionnaire given to the approached samples with the help of the respective organizations and a smaller number of samples belonging to the participating organization, a structured questionnaire of executive interviews were asked from senior leaders of the selected organizations. The questionnaire was constructed on the basis of the existing scales of the business analytics and strategic management literature, but had taken the items as the context of this study. A measure of performance outcomes were captured using secondary data, collected

from perceptual instruments by survey in addition to information derived from objective performance outcomes recognized sources like organizational reports, business intelligence dashboards, annual reports and industry data bases.

All the research model variables were collected. The organization-level variables were organizational size (by number of employees and annual revenues), industry sector and business analytics level of adoption. Analytics capability variables included ones related to the use of big data, data quality, predictive analytics capability, and data visualization practices. The variables implemented in the decision making process were decision making speed and effectiveness of strategic planning. The performance outcome variables included operational efficiency, financial performance, innovation capability, competitive advantage and overall organizational performance. Each perceptual item was rated on five point Likert scaled ranging from "strongly disagree" to "strongly agree" and with a higher score representing higher level in the construct measured.

Data Pre-processing and Data Quality Assurance

After a systematic data pre-processing procedure, which guarantees the data quality and suitability to planned data analysis methods, the collected data were analysed. No corrections were made for missing data items and continuous data where there was incomplete data was filled with median values for that item (conservative approach which is less likely to be influenced by outliers data points). The responses were coded and data validated for consistency in responses and categorical data was appropriately transformed for use in regression models.

There is outlier detection based on the Inter Quartile Range (IQR) method, an outlier is a data value that is outside of the middle 50%. This is considered a good method for uncovering very few extreme data that might have significant impact on statistical estimates, (e.g. chief Barnett & Lewis 1994). All continuous variables were then subjected to outlier detection and Min Max normalization to ensure the data was constrained between 0 and 1 to enable scaling in comparison to the same measurement made on constructs with different raw measure units. There was a reliability assessment using Cronbach's alpha, and a score of ≥ 0.70 was deemed as having a minimum acceptable value for internal consistency (Cronbach, 1951). This was surpassed in all constructs in this study, thus demonstrating the reliability of the measurement scales.

Statistical Analysis Techniques

Analysis of the data had already passed through various stages in order to answer particular questions of the study with hypotheses. The means, standard deviations and frequency distributions informed about the sample characteristics and general outlines of the main variables. To get some initial evidence of the hypothesized relationships, the bivariate relationships was examined by Pearson correlation analysis.

Multiple linear regression was used to uncover the important determinants for strategic decision-making effectiveness. Strategic decision-making effectiveness was used as the dependent variable and business analytics capability, data quality, predictive analytics capability, and data visibility and visualization practices as the independent variables. The relative contributions of each predictor to the model were calculated by estimating the regression coefficients (α) along with the corresponding t -values and the coefficient of determination (R^2) was used to assess the amounts of variance in the dependent variable accounted for by the model.

To analyze the dimensionality of the measurement items the dimensionality reduction analysis was used and the structure of the measurement items was examined in the analysis by Principal Component Analysis (PCA) with varimax method. It is a technique that is commonly used in the process of scale development and scale validation to discover the latent factors underlying a covariance among the observed variables (Abdi & Williams 2010). The factor structure obtained was then evaluated by Confirmatory Factor Analysis (CFA) based on the measurement model, tested with AMOS software, to obtain a good fit.

The analysis technique from the most basic in terms of theory was used in the form of the structural equation model (SEM). This study is most appropriate for the use of SEM, which would allow estimation of a number of regression equations and would enable consideration both direct and indirect relationships between constructs (Abd-El-Fattah, 2010). The model fit was analyzed using several fit indices, such as the chi-square per degree of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI) and Root Mean Square Error of Approximation (RMSEA). Measuring model fit as suggested by the work in the SEM literature (Hu & Bentler, 1999), a CFI of > 0.95 and TLI of > 0.95 with RMSEA < 0.06 were deemed acceptable model fit.

Evaluation Indicators & Software.

Multiple indices were developed for the key constructs in the theoretical model. The Business Analytics Maturity Index scores are derived by taking the sum of all the scores from each of the aforementioned components of analytics adoption, predictive capability and data governance and visualization practice and using those scores as their respective weights. The Strategic Decision-Making Effectiveness Index (SDMEI) is a tool for quantifying the perceived effectiveness, Delphi speed and impact of strategic decisions. The measures reflecting the operational efficiency of the Organization were part of the Operational Efficiency index. The Financial Performance Index incorporated indicators that reflect financial performance of the Organization. Other metrics included data quality, predictive analytics skills, innovation performance and competitive advantage. In order to be conveniently interpreted and compared across organizations, all the indices were scaled to a range of 0-100, using the methods suggested by Danilov et al.

Data were analyzed using a suite of a number of software which were selected because of the complementary strengths they have. Data were analyzed using SPSS version 29 including: pre-processing of data, descriptive statistics, correlation and multiple linear regression analysis. For this purpose AMOS was used to perform CFAs and SEM tests which includes the usable graphical interface and the algorithms for the estimation of complex path models. Further statistical analyses and data visualisation were performed using R version 4.3, in addition to which R has a large collection of packages that are there for advanced statistics. Microsoft Power BI was used to generate interactive dashboards and visualizations of the results and Microsoft Excel was the key application used in preparing the data and doing preliminary computations.

Results

The results of the statistical analysis are addressed in each of the following sub-sections, with participant characteristics and extent of business analytics usage of the sampled organisations being described. After that, the results of the regression and the correlation analysis are presented along with the results of the SEM in order to validate the hypothesized relationships between the constructs of analytics maturity and the strategic decision making outcomes.

Participant Characteristics

The final analysis included 972 valid answers, after following data cleaning and data processing as stated in the methodology. A cross sectional and generalise design was used and the sample consisted of different industrial sectors. As shown in Table 1, the most predominant sector in study is manufacturing which has 30.6% of the participating organizations. Next on the list was 27.8% service organizations, then 18.9% information technology organizations. The financial institutions was the largest sector at 12.7% and healthcare was the smallest sector at 8.0%. This distribution is proportionate both between industry sectors of traditional industries and service-oriented industry sectors of knowledge driven businesses and meaningful comparisons of analytics practices and outcomes based on industry sector within different environmental contexts are made.

Table 1. Distribution of participating organizations by industry sector

Industry Sector	Percentage of Sample
Manufacturing	32.6%
Service	27.8%
Information Technology	18.9%
Financial Institutions	12.7%
Healthcare	8.0%

The respondents were selected according to multiple levels from the hierarchy of each organization. Around 15% of the respondents included senior executives, such as chief executive officers, chief information officers and chief data officers. When working together, the number of business analysts and data scientists was the largest, at 35%, showing that they are both vital in the implementation and day-to-day use of analytics tools and techniques. The other 50% of respondents were operations managers and department heads, which gave insights into the operational integration of analytical outputs in processes that lead to decision making. This multi-level sampling approach was in line with the best practices in organizational research such as trying to collect data from informants spread across various hierarchical levels of the organization, so as to get a holistic view of organizational phenomena (Ghauri et al. 2020). According to organisation size the samples were small and medium size enterprise (SME) and large corporations. The segment of the sample below 250 employees had 28% (23 companies), between 250 and 1,000 employees had 45% (24 companies) and more than 1,000 employees had 27% (23 companies). Given the prior research that has found that the impact of business analytics on business decisions can vary according to maturity level and also resource availability at various organizational-levels, all the results obtained here are extrapolated and presented for various resource levels and organizational sizes. For another argument about the diversity of the sample, the annual revenue of the participating organizations ranged from under \$10 million to at least over \$1 billion while the median annual revenue was roughly \$150 million.

Among the highlights for the sample, nearly a third of companies are employing some type of business analytics platform. The raw research notes is divided by whether the organizations used business analytics platforms or not; 84.5% of the organizations were currently users of business analytics platforms. This high adoption rate may be a result of both the current business climate, and the fact that many organisations in many Business Sectors are in the midst of building analytics infrastructure to support data-informed decision-making (Davenport & Harris, 2017). Both adoption and the level of maturity in analytics capabilities are, however, not sufficient to guarantee business performance; the strengths of data governance, practices and implementation are relevant to the level of success in

analytics investments, as shown in the next analysis. In the subsequent subsections, it can be used as a solid foundation to look into relationship between the analytics maturity, effectiveness of taking decision and organizational performance.

Business Analytics Adoption

Focussed upon the extent and nature to which the sampled organisations embraced business analytics, this was explored to give context to the assessment of the relationship between the maturity the organisation aimed to reach as a result of applying business analytics and impact on business decision making. The overall findings indicate that organizations are not only focused on investing in their data-driven efforts, but that they are also highly engaged with different analytical methods or tools. Specifically, 81.7 % of the enterprises that participated reported having business intelligence dashboards to monitor the key performance indicators and to inform the business decision making process – one of the basic business intelligence tools (Chen et al., 2012). The level of adoption indicates that organizations understand the importance of having real-time data visualization for their enhanced managerial awareness and response.

There are lots of organisations that have embraced much more advanced analytical processes than simply reporting. Its research revealed that 76.9% of organizations used predictive analytics for strategic planning; these used statistical modeling and machine learning algorithms to predict trends, risk and opportunities (Siegel, 2013). The outcome is similar to recent literature in strategic management in which there is a greater focus on the transition towards a “predictive” orientation, with the predictive likenesses leading to a certain edge in competition (Adesina et al., 2024). Additionally, 73.8% of firms employed data visualization tools specifically for executive decision-making process; organizations invest resources in developing easy to use interfaces where gigabytes of data become information that is easily usable for rapid decision making by the executives (Tufte & Graves-Morris, 1983).

Half of the organizations (69.6%) said they utilize big data analytics against major business processes and business strategies, reflecting the significance of leveraging large and diverse data sets for business to drive operations and decision making. It is significant because the factors in big data management—such as volume, velocity and variety—indicate that robust infrastructure and expertise is needed. Also, 71.2% of organizations had formal data governance policies and procedures, highlighting the significance of having policies and procedures in place for data quality, security and compliance (Batini & Scannapieca, 2006). The significance of such frameworks is they ensure that increased trust in the analysis products come from reliable and trustworthy data, ultimately increasing the trust in the recommendations produced from the data.

The degree of commitment to business analytics within your organisation is good, with the majority adopting 2–3 complementary tools and practices. But as the ensuing analyses will reveal, not everything analytics technologies are doing is creating more successful strategic outcomes. These investments are likely to work if analytics is developed and ready to use, data is of high quality and is grounded in an organizational culture that promotes evidence-based decision making (Grossman, 2018). This differential in adoption also indicates that organisations may be at differing stages in their Analytics maturity journey, with some just starting on the basis of building basic tools such as dashboards and others have been more advanced and are working on more sophisticated predictive and governance tools. To enable the differences in impact of the different dimensions of analytical data to be analysed in the following regression and structural equation modelling, this grading was used.

Organizational Performance Outcomes

We studied the gains, across five metrics (strategic decision quality, operation efficiency, financial performance, innovation capability and competitive advantage) that the companies were able to achieve in order to understand the actual gains of the business analytics maturity. All the results presented (Table 2) are meaningful and long-lasting from all points of view of the various indicators measured, and demonstrate the strategic value of data-driven management unmistakably.

Table 2. Organizational performance outcomes associated with business analytics adoption

Performance Indicator	Improvement
Strategic Decision Quality	+30.2%
Operational Efficiency	+27.4%
Financial Performance	+23.8%
Innovation Capability	+22.5%
Competitive Advantage	+21.7%

The biggest gains were seen with the ability to make strategic decisions, with adoption of advanced analytics capabilities rising by 30.2% compared to those that had not adopted advanced analytics. The finding is the importance of strategic decision-making and its ability to be data-informed, precise and timely (Davenport & Harris, 2017). When these tools and technologies are combined, the decision makers will have time to consider different options, see through results and allocate resources to priorities in their organization. Importantly, this improvement is most noticeable in cases where this is the case, suggesting that organisational maturity for analytics can affect the deliberative process of the organisation in a fundamental manner.

The operational efficiency impact was also featured in the top three and perceived gains as 27.4% for O2. With analytics now providing a vital piece of the puzzle that is already working for this fundamental success, other research has pointed to significant benefits in cost reduction and productivity improvement by leveraging analytics through the power of optimising process, supply chain and resource allocation (Schmarzo, 2013). The integration of big data within enterprises will enable them to detect inefficiencies, optimize workflow and eliminate wastes to get better performance in their operations in general (Shmueli et al., 2016). According to our calculations, operational efficiency is more than just a result of using analytics; it is a real operational excellence.

Case studies illustrate that the positive contribution that analytics brings to revenue, profitability and cost management is clear, as financial performance was enhanced by 23.8%. The findings found good correlation with the resource-based view theory concluding that a practitioner's business could have a competitive advantage in the market if its capabilities could be added value and rare in the market, as could generate a high business profit (Grant, 1991). More highly developed analytics programmes can be used to identify market opportunities, optimise pricing and minimise financial risk, all of which are factors which boost the bottom-line performance of the business (Langer, 2025).

On the Innovation capability measure, which aligns with growing skills in analytics, a 39% increase was observed, reinforcing the notion that developing analytics maturity, supports an experimental culture and discovery culture based on data. By analysing customers, customer behaviour, market trends and operations, organisations can brainstorm new ideas for products and services, discover the unmet needs of their customers, and accelerate their new product and services development processes. This

new finding reinforces the usefulness of analytics as an innovation and organizational learning tool (Eisenhardt & Martin, 2017) and as an optimization tool.

Finally, on the level of competitive advantage, the increase was 21.7% as expected because with the usage of analytics matured capability one organization can take the advantage of competition. The benefit of this is you will make better and faster decisions and are able to react to market changes proactively and provide customers with value added services (Davenport & Harris, 2017). As each of the performance dimensions regularly gains ground, it offers strong evidence that business analytics maturity is a vital factor in the success of organizations from a strategic, operational, financial and innovation perspective.

Regression Analysis

To see the influence of those factors likely to enhance the effectiveness of strategic decision making in the proposed data based management system, multiple Linear Regression was conducted. The dependent variable in this model was Strategic Decision-Making Effectiveness Index, which was an overarching score reflecting the perception of the quality, timeliness and effectiveness of the strategic decisions. These independent variables encompassed four key aspects of the business analytics maturity: business analytics capability, data quality, predictive analytics capability and data visualization practices. The chosen predictors were determined by the theoretical model created during the literature review, that all these dimensions are uniquely connected to improving strategic decision-making (Davenport & Harris, 2017) (Dietrich et al., 2014).

The model was also found to be highly explanatory with .764% of variance in strategic decision-making effectiveness explained. The average of the four predictor variables related to analytics is CoD = .96, meaning that all of the explanatory factors present in organizations for making strategic decisions are covered by the four predictor variables. The adjusted value was still high: 0.760 indicating the model's ability to explain is not a spurious effect of overfitting. The overall model was significant (); the set of predictors accounted for a significant proportion of the variance of the overall model of decision-making effectiveness.

The relative importance of each of the predictors can be seen in individual regression coefficients when reviewing the results of the regression as displayed in Table 3. The most important predictor emerged as 'capability in business analytics' which massed a standardized coefficient of (). This discovery shows that the organization's value chain—from the technology, the analytics and tools, to the people, that enable effective strategic decisions—is an important component of an analytics consolidation effort. Companies that have taken a step further with their analytics can find the data, process it and use it to gain insight, making decisions on the go.

Table 3. Multiple linear regression results predicting strategic decision-making effectiveness

Predictor Variable	Standardized β	p-value
Business Analytics Capability	0.47	< 0.001
Data Quality	0.41	< 0.001
Predictive Analytics	0.36	< 0.001
Data Visualization	0.30	0.002

Data Quality standardized coefficient (.) was the next most important predictor. This shows the importance of having correct and accurate information for any analyses on it as information is the basis for any analysis to be undertaken (Batini & Scannapieca, 2006). More so than any other aspect of any analytical tool, regardless of the sophistication, the health of the data stream it's meant to analyze becomes a critical determinant of the quality of its results, its outcomes, and, further, the decisions it is designed to inform. But, with a data quality of that magnitude, it's essential that organisations put resources into building more effective data governance programs, data cleansing processes and data stewardship practices to confirm their analytical outcomes are held to the very highest standards of data quality.

Another key predictor (prime) was the ability to access a capability for predictive analytics. To conclude, such a finding reinforces the need for accurately predicting future events and assessing risk and outcomes from statistical models and machine learning techniques, which are important tools in strategic planning (Siegel, 2013). While Addressing issues before they even arise is one of their responsibilities, Predictive Analytics enables them to do so: so long as they do not fit in inside their, Predictive Analytics provides data-based insights into trends and potential issues that might emerge in the future.

The standardized coefficient () of data visualization practices was relatively small and was still one of the most important predictors. This discovery shows that interactive dashboards, charts and other visual analytic features can help decision-makers better communicate data patterns, but aren't quite as powerful as the other, more elemental, suite of analytics and data quality (Tuft & Graves-Morris, 1983) features. Perhaps, it's because imaging is often a parallel mode of capability, supporting other analytics investments, and a way to maximize those investments, that it is frequently discovered part and parcel of this capability.

There was also a check for multicollinearity of the predictors during the regression analysis. The values of variance inflation factor (VIF) did not exceed 3.0 and multicollinearity was not significant; thus, the coefficients estimated for these four predictors were reliable. A Durbin Watson statistic near the ideal 2.0 was indicative that the assumption of an independent dispersion was met. These tests contribute to the acceptance of the conclusions and results for the regression.

Correlation Analysis

Pearson correlation was used to examine the relationships among the constructs involved in the proposed data-driven management framework to consider the bivariate relationships between key variables. This analysis gives some preliminary evidence for the hypothesized relationships between business analytics maturity, and different aspects of organizational performance and aims to serve as a basis for the subsequent analysis based on the structural equation model. As expected based on the theory, there are high and positive, and statistically significant, correlations between all core constructs and increased analytics maturity with increased strategic and operational success, as indicated in Table 4.

Table 4. Pearson correlation coefficients among key constructs

Construct	1	2	3	4	5	6
1. Business Analytics Maturity	1.00					

Construct	1	2	3	4	5	6
2. Strategic Decision-Making Effectiveness	0.84*	1.00				
3. Organizational Performance	0.80*	0.78*	1.00			
4. Innovation Capability	0.77*	0.75*	0.82*	1.00		
5. Data Quality	0.72*	0.69*	0.65*	0.61*	1.00	
6. Predictive Analytics Capability	0.68*	0.66*	0.63*	0.59*	0.55*	1.00

Note: All correlations are significant at $p < 0.001$.

The relationship between business Analytics maturity and the strategic decision making effectiveness appears to be highly positively correlated, at (.). More sophisticated measures of an organization's maturity for analytics – its use of more advanced data infrastructures, its more knowledgeable users on the analytical team, and its more effective analytical governance – are correlated with the quality of the organization's strategic decisions (Davenport & Harris, 2017). This correlation is remarkable in particular because of its strength: Analytics maturity explains more than 70% of the variance in decision making effectiveness and is a critical component of the strategic management process (Dietrich et al., 2014).

The correlation between business analytics and the performance of the entire organization also had a strong positive correlation of (.). But this finding provides solid proof that improving products' operational effectiveness, treating products' financial results, and enhancing products' competitive outcomes are interrelated with investments in decision products' analytic capability (Grant, 1991). In the same way, there was also a significant correlation between analytics maturity with innovation capability (= 0.52) suggesting analytics based organizations evidence that they are more likely to identify new opportunities, conduct new product tests and get products and services to market (Eisenhardt & Martin, 2017). This finding aligns with the previous research demonstrating that using analytics is an accelerator for nurturing 'experimental to learn' attitude and testing assumptions (Adesina et al., 2024).

Analyzing the interrelationships between the performance outcomes themselves, the correlation coefficient between the effectiveness of the strategic decisions and the organizational performance was equal to () and correlation coefficient between the effectiveness of the strategic decisions and innovative capacity of the organization was equivalent (). For example, improved decision making can have a variety of impacts on the success of an organization—and the value of such positive impacts can extend to better performance, which can perpetuate the value of decision-making practices based on data (Loshin, 2012). The relationship between organizational performance and organisational innovation capability on this index was particularly high at (), that is, both are closely linked with the innovative organisations showing a tendency to better overall performance outcome.

The relationships between the different components of the analytics maturity and the outcome variables were also analysed using the correlation method. The findings of the qualitative survey on the analysis of data quality showed that the quality of data was found to have significant relationship with the effectiveness of strategic decision making (,) and organizational performance (,), thus reinforcing the need to have quality data to provide quality analytics (Batini & Scannapieca, 2006). Likewise, decision making effectiveness and organizational performance showed predictive analytics capability,

reflecting the significance of organizations ability to make decisions based on predictive analytics, which is also crucial for strategic planning as per Siegel, 2013. However, there is a moderate correlation between predictive analytics capability and data quality, indicating that, although correlated, they are independent components of analytics maturity that are both important inputs to organizational outcomes.

The results of this correlation provide a positive initial hypothesis about the relationships in the information-led management system. At all business data maturities measured, business analytics revealed statistically significant medium-to-high correlations with each pair, indicating there is more to business analytics than its role as an auxiliary function of the organisation, as it is one of the major influences on the effectiveness of business decisions and organisation success. The pattern of the correlations also shows that the various dimensions of analytics maturity – data quality maturity, predictive maturity, visualization maturity, business maturity, etc. – seem to present some level of synergy; that is, they seem to reinforce one another, with positive synergy, so that the theory will be addressed further with structural equation modeling in the following subsection.

Structural Equation Modeling

With the basis of data, structural equation modelling (SEM) was rigorously tested to connect the hypothesised causal pathway in the proposed framework. The analysis could also be used SEM to provide the estimation of at least two or more regression equations, and study the direct and indirect relationship between the latent variables (Abd-El-Fattah, 2010). The Confirmatory Factor Analysis (CFA) was used to test the model measurement and the test result showed that the indicators loaded were significant and the factor loading was more than 0.70 and significant (). The CFA results served as an adequate basis to continue working with the structural model—which posits the hypothesized relationships between business analytics maturity, strategic decision-making effectiveness and organizational performance.

Several goodness-of-fit (GoF) indices were used to gauge the overall fit of the structural model according to the recommended criteria in the SEM literature (Hu & Bentler, 1999). The ratio of chi-square per degree of freedom was equal to $\chi^2/df = 2.02$ and was much smaller than the recommended value of $\chi^2/df = 3.0$, indicating good agreement between the model hypothesized and the observed results. The proposed model fitted of a comparative fit index (CFI) was 0.98 which is well above the 0.95 criterion and shows that the proposed model is a significant improvement over a null model with no relationship among the constructs. Tucker–Lewis Index (TLI) was also validated the model fitting, it was 0.97 while index is more than 0.95. Last but not least, the Root Mean Square Error of Approximation (RMSEA) was 0.042 with a 90% confidence interval of 0.038–0.046, which is much lower than the suggested value of 0.06. As the RMSEA value is very low, the covariance matrix matched the covariance matrix in the model very well. These fit indices can be combined to ensure high confidence about the structural model's ability to capture the relationships among the constructs in the data-driven management framework.

Path coefficients estimated using the SEM model showed that there were significant direct effects that were related to the results of the multiple linear regression analysis. Strategic decision making effectiveness exhibited a significantly positive direct effect on the level of business analytics maturity (Direct Support: +, –). It indicated that the more mature the business analytics, the more effective their business decisions will be within the strategic area. Effectiveness of strategic decision-making on organizational performance was then a positive direct relationship having a high impact, such that the better the quality of the strategic decision making, the higher the organization's performance – both

operational, financial and innovation. In addition, indirect effects, cascading through the mediator of strategic decision making effectiveness on organizational performance were found to be statistically significant at odds to the direct ones (from +1.00 to -13.30) reinforcing the important mediating role played by strategic decision making. This finding supports the theoretical premise that analytics will be of no use in directly improving performance but rather simultaneously the performance improvement will come as part of the effectiveness of the strategic decisions (Davenport & Harris, 2017).

The connections between individual components of analytics maturity were also analyzed in the SEM analysis. Predictive Analytics is indeed known to have a significant positive correlation with other data quality characteristic, which further confirms that predictive analytics will not be possible without achieving good data quality, or will be challenging if the data quality issue is not addressed (Batini & Scannapieca, 2006). The practice of data visualisation was also positively affected by the capability of predictive analytics, meaning that organisations with high capability of predictive analysis are more likely to use a visualization tool that makes use of the output from the prediction (Tufte & Graves-Morris, 1983). The sequential relationships between these analytics maturity dimensions illustrate the interdependent relationships between the habilites, with less advanced capabilities in data management giving way to more advanced analytical capabilities, aided by better visualization.

Additionally, there are the multiple correlations (ANSWER) associated with the endogenous constructs in the model that also show the goodness of fit. The combined effect of the dimensions of analytics maturity accounted for 82.4% of the variance in strategic decision making effectiveness, showing that the overall analytic maturity dimensions explain a large portion of the variance in decision-making effectiveness. What's more, the model explained 78.9% of the variance in organizational performance, and proved to be a robust mediator between the analytics maturity level and the organizational performance. These high values in business analytics maturity indicate high maturity points and excellent model fit indices justifying the proposed data-driven management framework and validate the business analytics maturity as a key enabler in strategic decision making and organisations success.

Comparative Findings

In alignment with the findings of this study that the results validated that business analytics has become more instrumental than traditional BI in business organizations, a comparative analysis was conducted between an advanced capabilities group and a low group of analytics maturity for a final validation of the effect of business analytics maturity on business outcomes. It is an example of where the different sophistication of analytics is going to make a difference in performance, plus actual instances of where this difference in sophistication can be used to inform them of the potential return on investing in analytics. As outlined in Table 5, those organizations which performed better on the measures of advanced analytics were also found to perform better on all the performance indicators evaluated.

Table 5. Comparative performance outcomes: Advanced vs. low analytics maturity organizations

Performance Indicator	Improvement in Advanced Maturity Organizations
Strategic Decision Quality	+30.2%
Operational Efficiency	+27.4%
Financial Performance	+23.8%
Innovation Capability	+22.5%

Performance Indicator	Improvement in Advanced Maturity Organizations
Competitive Advantage	+21.7%

The greatest difference in score was in strategic decision quality, in which the high-maturity organizations scored better than the low-maturity organizations by 30.2%. This large attitudinal gap holds great potential for the future, as analytics matures, it can influence successful, informed and timely decisions on strategy (Davenport & Harris, 2017). They can more easily filter through the data, explore the more difficult strategic decisions, predict shifts in the market and more easily combine resource allocation with strategic plans for growth (Dietrich et al., 2014). The size of this gap suggests a tremendous opportunity to impact the manner in which organizations make key strategic decisions if maturity in the field of analytics can be achieved.

The greatest difference was identified in operational efficiency—the advanced- organizations seemed to operate 27.4% more efficiently than their low counterparts. This adds to previous study findings that can yield significant savings and increase productivity through investing in analytics to optimize processes, supply chain management and resource allocation (Schmarzo 2013). Data-driven insights can help pinpoint inefficiencies, optimize processes and minimize waste, thereby boosting overall performance and driving better results for organizations that have more developed analytics capabilities (Shmueli et al., 2016). The inefficiency in the operational efficiency analysis suggests that being an advanced analytics team isn't only about making strategic improvements – it's about being efficient on a day-to-day basis as well.

Significant financial performance differences – 23.8% – are clearly driven by the effect advanced analytics can be having on the revenue opportunity, profitability and cost management. This corresponds with the resource-based view which suggests that distinctive organization capacities, which include advanced analytics, came with worth and rarity and as a result shields a competitive advantage can improve their monetary outcomes (Grant, 1991). The deeper they are able to drill down into these analytics, the more money they will make on the bottom line – which benefits retail businesses in their ability to see market opportunities that they can exploit, optimize pricing, and limit financial risks (Langer, 2025).

22.5% of organizations with high maturity outpaced the rest of the respondents in terms of innovation capability, indicating that an analytics maturity culture is conducive to an experimentation and discovery culture through data. Understanding gaps, generating new ideas and accelerating the journey of product development and service creation can be achieved by analysing customer data, market trends, and operational information (Adesina et al., 2024). The finding confirms the concept that not only is analytics essential with regards to doing optimization but it could also be pivotal to innovation and organizational learning (Eisenhardt & Martin 2017).

Finally, an advantage gap was identified that equates to an analytics maturity advantage of 21.7%, likely pointing to some advantage to being able to differentiate from the other competitors. The upside is that they can make quicker and more very precise judgments, make better decisions when faced with changes in the market, offer greater value to their consumers (Davenport & Harris, 2017). Improvements achieved across all of the five performance indicators by organization, are considered indicative of business analytics maturity, driving success for the organization across strategic, operational, financial and innovation domains. The findings from the comparative analysis support and elucidate the regression results and the structural equation modeling results with a very apparent and

tangible example of how analytics maturity levels impact performance between organizations, further reinforcing the need for organizations to invest in developing their advanced analytics attributes.

Discussion

The following are important implications for strategic management and business analytics theory and practice resulting from this present study: From SEMs, the theoretical implication should take into consideration that the business analytics maturity is linked to the strategic decision making effectiveness and also demonstrates that business analytics is an asset to an Organization and is difficult to copy. One could infer from SEMs that business analytics maturity is related with the effectiveness of strategic decision making, and that business analytics is a valuable asset that cannot be reproduced in any organization easily (Grant, 1991). The variance of the model in the regression model is 76.4%, but 82.4% in the structural model, suggesting that a proposed framework explains “most part” of the variance in the data-driven practices and organizational outcomes. Further, there is strong mediation in the relationship between analytics maturity and organizational performance in the first link (between analytics maturity, and strategic decision-making effectiveness), suggesting that analytics investments can fail to impact on organizational performance, but in doing so, help organizations to make better strategic decisions. This finding raises the question whether it is technical knowledge that is the source of the success or it is through practical use of the insights gained that value can be added to a business. (Davenport & Harris, 2017).

On a more practical level, the results can inform organizational leaders, managers and policymakers of steps they can take to enhance their data-informed decision-making. The assumption of effectiveness: that the greatest contributor to strategic decision making effectiveness comes from business analytics capability is characterized by a standardized coefficient of 0.47, meaning that organizations should strive to invest in building their more complete infrastructure of analytics capabilities: the data platform, the analytical and data tools, and the analytical and data experts. The next important data quality predictor (with criteria score of 0.41) is the necessity to create proper data governance tools and to implement and respect strict data cleansing methods, and to establish data stewards who can safeguard the quality and integrity of information used for analytics (Batini & Scannapieca, 2006). Consequently, the practitioners can develop a packaged-investment Roadmap, with the simplest step of fixing more fundamental data problems, followed by the accumulation of predictive analytics and lastly investing in tools that would help visualize the data in a way that decision makers can easily access. To educators and trainers at schools, the results provide evidence of the value of developing business school courses to incorporate analytics maturity assessment tools and data governance in order to prepare students for the effective data management of organizations based on analytics.

While there is empirical evidence in support of the framework, numerous methodological concerns are acknowledged in imprinting conclusions from the results. It was a cross sectional type because it enabled researchers to collect data from a large and diverse sample of 200 organizations, although these data do not necessarily provide definitive evidence that could be used by researchers to determine which factors might have an effect on the role of a company's analytics maturity on its organizational performance. Even though the results of the structural equation modelling approach provide more evidence for causal pathways than does simple correlation analysis, longitudinal studies would be required to establish the directionality of the observed relationships as well as to understand how the relationships develop over time as organisations journey through the analytics maturity stages, as proposed by Abd-El-Fattah (2010). Additionally, the key constructs are measured through self-reports, such as culture effectiveness in strategic decision and innovation capability, which can result in common

method bias (CMB) in this study, due to self-serving reporting, and overreporting of the benefits of analytics in organisations. However, because multiple informants (with different levels of the hierarchical organization studied) somewhat decreases the concern, in the future, objective performance data from enterprise resource planning systems or financial data from audited reports should be explored that could provide a triangulation with the subjective assessments. The sample is diverse across industry sectors but primarily includes organizations that already uses business analytics platforms (84.5%), which may bias the findings towards the organizations that are still at an early stage of their business analytics journey or those organizations in industries less dependent on data.

The findings herein, however, point to many avenues for future research outside of the scope of the current study, including longitudinal research documenting changes over time in the relationships between analytics capabilities, analytics decision making processes and analytics performance outcomes as analytics organizations venture to the next stage of the analytics continuum (from initial use to integration and on to extended use – long-term evolution and impact). It is likely that the development of analytics capability and its effect on organizational outcomes, as discussed above, is a dynamic process that can be better modeled using repeated measures designs and/or panel data analysis (Eisenhardt & Martin, 2017). Next the effect of the culture, leadership support, and change management within an organization also needs to be looked at as moderating between degree of analytics maturity and effectiveness of strategic decision making, since previous qualitative studies suggest that the culture could positively or negatively affect the successful adoption of the data driven way of working (DWO) (Grossman, 2018). Less research has focused on the role of analytics on SMEs, particularly when those firms are not equipped to invest in an advanced analytics framework; and there is not a lot of research that delves into what might buffer the effect of analytics on the decision making process on an industry-by-industry basis, such as regulatory requirements in healthcare and finance, and technology velocity within the information technology sector. Finally, research into any negative trade-offs or unintended consequences of an over-optimistic use of analytics, such as “analysis paralysis,” algorithmic bias and reduced managerial intuition, is recommended to attain a balanced and comprehensive understanding of the impact of data-driven management on the current organizational environment.

Conclusion

The goal of this research was to design and practically validate a framework to explain that there could be a positive relationship between business analytics maturity and strategic decision-making and organizational performance in the context of using the data source. The overarching research question was related to the role analytics capabilities, responsiveness to data quality, predictive modeling and data visualization can play when analyzing how each of these can collectively drive the quality of decisions and impacts on larger organizational outcomes. The Positive aspects of the Study are clear, business analytics maturity is a strong tool for enabling Evidence-based Strategic Management, accountancy in this model for more than 76% of variance in the decision making capability. The work contributes to existing knowledge by building on the current research around the relationship between the use of technology and its effects, which goes beyond a correlation with respect to the performer. The current research provides insights into the connection between investment in analytics, decision making and the actual successes of the organizations. This sense of the one-fits-all reinforced and evolved from the resource-based view centers on analytical maturity as a useful asset for the organization that can lead to improved decision making processes and thus a competitive advantage, but may not have an obvious operational impact.

Finally some directions for further research are clear from the limitations and gaps identified in this work, namely longitudinal studies that trace the changes in the capabilities of organisations at varying stages of maturity in analytics could be valuable in exploring how the focus of analytics capabilities shifts over time and what lag effect might the shift in the capability cause on the outcome measures would prove valuable. Also, the role of other institutional forces in an organization such as the organization's culture and leadership commitment and its change management practices could moderate the relationship between an organization's investment in analytics and the resulting effects. Balanced assessment of potential negative effects, such as analysis paralysis and loss of management intuition, are important for approaching the use of analytics in strategic management with a thought-out perspective. The answers to these questions can help to shed light on the potential for wider use of data to inform better business decision making and to provide sustained competitive advantage in today's data-rich business landscape for future research.

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