

Business Analytics and Data-Driven Decision Making in the Era of Big Data

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Abstract

In light of the growing use of big data and analytics, the process of making business decisions is evolving towards being informed by evidence and efficiency. The purpose of this paper is to identify how such factors like descriptive, predictive and prescriptive analytics, application of AI and ML technologies and use of big data platforms influence the quality of decisions and organisational performance. Applying a quantitative methodology, data were collected from 250 managers in various industries including manufacturing, IT services, retail and finance. Regression analysis and SEM model were used to identify relationships. As the results show, predictive analytics ($\beta = 0.42$, $p < 0.01$) and prescriptive analytics ($\beta = 0.36$, $p < 0.05$) have the most effect on decision quality, while SEM confirms a strong relationship between Analytics Capabilities $\rightarrow$ Decision Quality ($\beta = 0.71$, $p < 0.001$) and Decision Quality $\rightarrow$ Organisational Performance ($\beta = 0.63$, $p < 0.001$). Moreover, an indirect effect from analytics capabilities on organisational performance ($\beta = 0.29$, $p < 0.05$) was identified. The results provide support for the assertion that companies with greater analytics maturity make more accurate and evidence-based decisions leading to higher levels of operational efficiency and innovation. Implications for managers are that there is a need for emphasis on analytics infrastructure, training and development, as well as data governance to enhance the potential for gains from adopting analytics. The limitations of this study are that it is cross-sectional, based on self-report data, and limited to a particular industry.

Keywords: Business Analytics; Data-Driven Decision Making; Big Data; Predictive Analytics; Organisational Performance; SEM; Decision Quality.

I. INTRODUCTION

There have been some major developments due to the exponential growth in the quantity of digital data over the recent years. Due to the fact that such data can be generated through multiple sources like social networking sites, IoT devices, internally through their own systems, or even externally by customers, organizations face a situation where they must confront such data. Therefore, the ability to analyze such data has become imperative in the current organizational environment (Vassakis et al., 2017; Chen et al., 2012).

More and more people understand that data driven decision making is the methodology that can be used for gaining competitive advantage. Utilizing analytics within managerial processes enables firms to become more efficient, to innovate, and to make more accurate decisions

regarding their strategic choices (Ajah & Nweke, 2019; Mikalef et al., 2020). Specifically, implementing predictive and prescriptive analytics enables firms to forecast changes, minimize risks, and respond to emerging customer needs (Pappas et al., 2018; Alsghaier et al., 2017).

However, in spite of growing popularity of the topic, some weaknesses might be discovered within the present scope of scientific works dealing with empirical research focused on the influence of maturity of business analytics on decision-making quality (Soldić-Aleksić et al., 2020; Vera-Baquero et al., 2015). In other words, the current research papers seem to focus on implementation of technology or process optimization, yet fail to take into account comprehensive influence of maturity level of the phenomenon mentioned. Another important thing is that different aspects should be considered while discussing the issue raised, such as organization size, organizational culture, and industry.

This study aims to bridge this gap through the examination of the effects of business analytics on decision-making and organizational performance. Specifically, it will seek to prove the link between the capabilities, processes, and outcomes associated with analytics in different sectors. The significance of the study lies in its theoretical and practical importance since it will contribute to the existing literature base on decision-making models enabled by analytics and provide practical insights for managers on big data capabilities.

This paper is divided into six sections. Following the introduction, Section 2 has a literature review and a theoretical frame. The third section will be on methodology. Section 4 will contain results and analysis. Discussion and recommendations will form Section 5. Conclusions and future research constitute Section 6.

II. LITERATURE REVIEW

Decision making using business analytics has gradually become an important component of modern decision-making within organizations, enabling them to analyze vast amounts of data generated from digital ecosystems (Ekka & Jayapandian, 2020; Gandomi & Haider, 2015). To this end, three types of analytics have been identified by scholars in the literature: descriptive analytics, wherein previous data is analyzed to establish patterns; predictive analytics, in which advanced statistical and machine learning techniques are applied to forecast future trends; and prescriptive analytics, in which recommendations are made to enhance decision-making efficiency (Hu, 2018; Wolniak & Grebski, 2023). These are some of the ways through which data can be analyzed in modern settings, and they mostly depend on big data systems like Hadoop and Spark (Zhao et al., 2014; Fosso Wamba, 2017).

Empirical findings have shown that there is a positive relationship between the application of analytics and organizational success (Waller & Fawcett, 2013; Kholmuminov et al., 2021). The employment of analytics is said to improve efficiency levels, stimulate innovation, and make sure that strategies are in line with the demands of the market. Additionally, the use of predictive and prescriptive analytics tends to improve decision-making, minimise mistakes, and lead to faster responses to any changes in the market (Duan et al., 2019; Reddy & Ramanadham, 2017). It is documented in cross-sector literature that organisations adopting high levels of analytics tend to have higher abilities to optimise their processes, mitigate risks, and allocate resources effectively (Wamba et al., 2017; Mira, 2024). On the other hand, there is evidence that suggests challenges

facing analytics adoption.

Recent academic works have shown the increasing significance of real-time analytics, cloud computing technology, and self-service in influencing data-informed decisions. AI-driven dashboards and edge computing systems help managers in monitoring their activities in real time and making necessary adjustments based on any anomalies found. The use of self-service analytics tools makes it possible for managers at different levels within an organisation to analyse data on their own, thereby encouraging a culture of data-informed decisions (Gunasekaran et al., 2017).

Despite the vast body of literature on analytics adoption, the relationship between analytics capabilities and their integrated effect on the outcome of decision-making processes has not yet been studied in depth. There is also limited research into the relationship between analytics capabilities and performance measures as well as how analytics capability varies across industries, organisation size, organisational culture, and managerial experience. These research gaps need to be bridged to enable development of frameworks for managing analytics.

III. RESEARCH METHODOLOGY

3.1 Research Design

In regard to the current study, a quantitative approach will be utilized to assess the impact of competencies in business analytics on decision-making and organization performance. This well-defined and structured approach facilitates the collection and analysis of data to provide an empirical basis for the theoretical framework presented.

Figure 1 provides a holistic model that depicts how organisations use analytics to improve decision-making and performance results. The first element is Data Inputs, which comprise internal data (transactional, operational, human resource, and finance-related), external data (market-, competitor-, and social media-related), and big data (Internet of Things [IoT]-related, clickstream, text, images/videos, and geo-spatial). The inputs undergo analysis using the Analytics Processes that include descriptive analytics, predictive analytics, and prescriptive analytics and the technologies that help include Hadoop, Spark, artificial intelligence/machine learning (AI/ML), cloud computing, and stream processing. The output of the process includes Decision Outputs, ranging from strategic, tactical, to operational decisions. In turn, these impact the Performance Outcomes along financial, customer, and organisational levels.

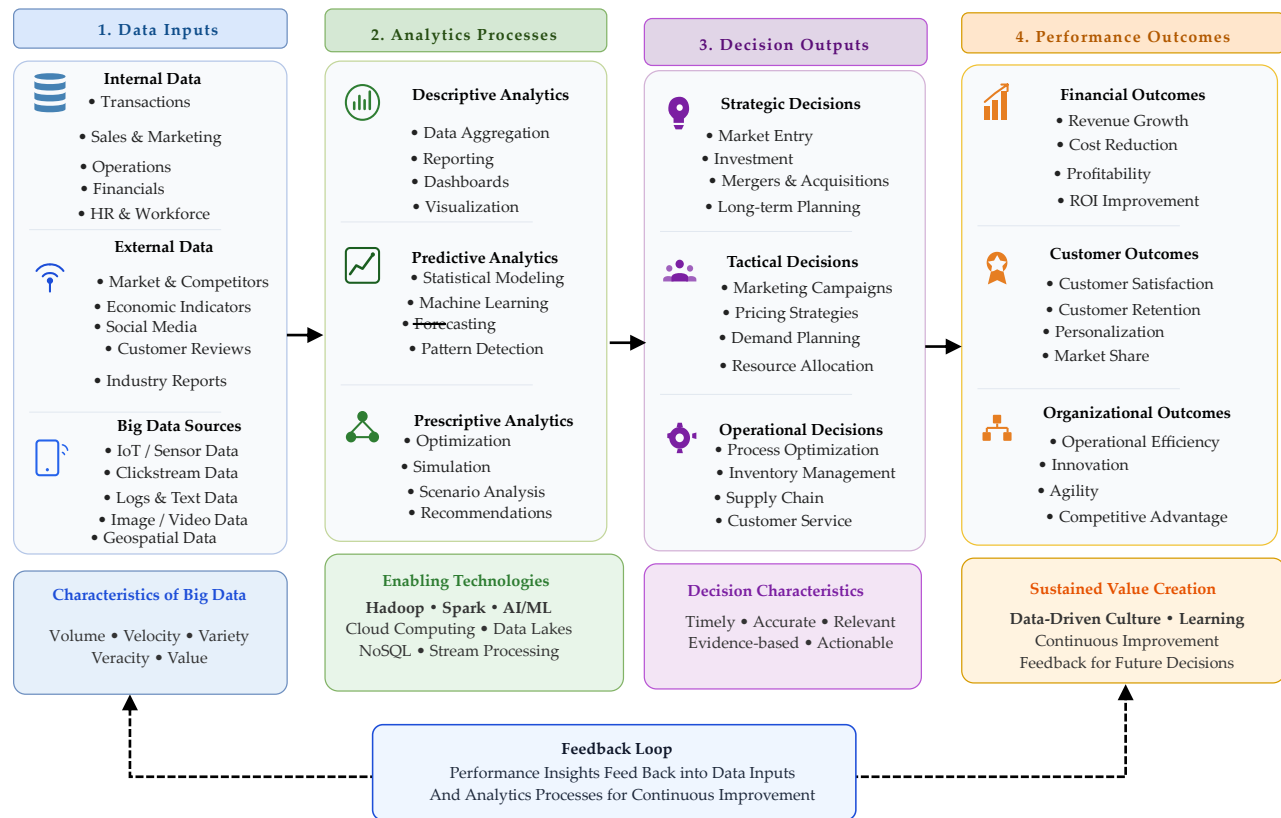


Figure 1: Analytics-Driven Decision-Making Framework

3.2 Population and Sampling

The respondents belong to managers of different industry segments such as manufacturing, IT, retail, and financial industries. The sample size was chosen randomly, with $N = 250$, through stratified random sampling. It includes middle-level and senior-level managers who make important decisions on a strategic as well as operational basis.

3.3 Data Collection Methods

The process of data collection was done through primary as well as secondary methods. Primary data were collected through a survey process which involved asking respondents certain questions on the use of analytics, decision making and organization's performance in general using the Likert scale method. It is worth noting that the inclusion of secondary data in the form of reports and publicly available information increased validity.

3.4 Analytical Techniques

Examples of methods that can be employed in order to test the research hypotheses developed within the theoretical framework include regression analysis and Structural Equation Modelling (SEM). In case of regression analysis, the aim will be to determine the direct correlation between the presence of analytics skills and the quality of decisions made. On the other hand, the SEM method will analyze the effect path that is produced by all variables.

3.5 Metrics

Key metrics for the study include:

- **Decision Quality:** in terms of accuracy, timely information, relevance, and making decisions based on evidence.
- **Operational Efficiency:** analysed by the means of process optimisation, effective use of resources, and reduced costs.
- **Organisational Performance:** measured based on results of innovation, financial indicators, customers' satisfaction, and competitive advantage indicators.

The described research design offers an empirical way of exploring the effects of business analytics on decisions and performance in various industries.

IV. RESULTS AND ANALYSIS

4.1 Analytics Adoption Metrics Across Sectors

Table 1 depicts the descriptive statistics for levels of business analytics implementation in various sectors such as manufacturing, IT, retail, and finance. Measures include the extent to which firms implement descriptive, predictive, and prescriptive analytics, as well as artificial intelligence/machine learning and big data analytics technologies such as Hadoop and Spark.

Table 1: Analytics Adoption Metrics Across Sectors

Sector	Descriptive Analytics (%)	Predictive Analytics (%)	Prescriptive Analytics (%)	AI/ML Usage (%)	Big Data Platform Usage (%)
Manufacturing	82	61	47	54	50
IT Services	91	85	72	78	80
Retail	77	68	55	60	58
Finance	88	79	65	70	68

Table 1 shows the use of different types of business analytics tools and technologies among four different industries – Manufacturing, IT services, retail, and finance. The industry that comes first in terms of the adoption of analytics tools is the IT services industry where 91% of firms use descriptive analytics, 85% firms use predictive analytics, and 72% firms use prescriptive analytics, thus demonstrating high maturity in analytics. The second highest use of analytics tools is observed among the finance companies where a high use of all the three analytics types as well as the AI/ML approach is noted. However, manufacturing and retail have shown relatively low use of both prescriptive analytics and AI/ML. Similarly, big data platform use by different industries also supports the above findings where a higher percentage of IT services and finance companies use platforms like Hadoop and Spark compared to manufacturing and retail.

4.2 Impact of Analytics Maturity on Decision Quality

As depicted by figure 2, analytics maturity is positively related to decision quality. The figure presents a graph that has analytics maturity at four different levels, namely Low, Medium, High, and Very High on the x-axis and Decision Quality (%) on the y-axis. It becomes evident from the graph that there is an upward slope, whereby the more mature organizations are, the higher decision quality they produce. This implies that organizations adopting advanced analytics

experience better results regarding accurate, timely, relevant, and evidence-based management decisions.

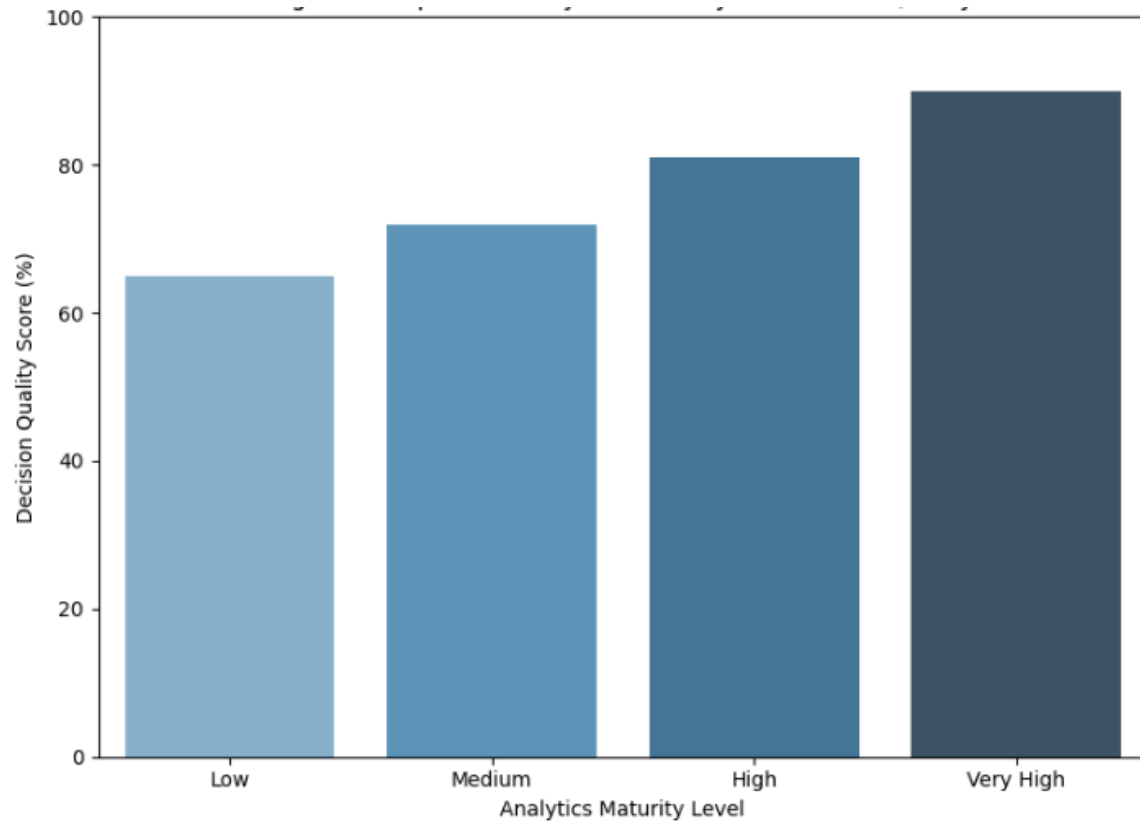


Figure 2: Impact of Analytics Maturity on Decision Quality

4.3 Summary of Patterns and Managerial Insights

Correlation Analysis: There is a significant relationship between the degree of analytics maturity and the quality of decisions ($r = 0.71$) as well as organisational efficiency and innovation ($r = 0.63$; $p < 0.05$).

Sector Trends: Sectors IT and finance perform better than manufacturing and retail regarding adopting analytics and making decisions, emphasizing the significance of sector-wise analysis.

Accordingly, the findings suggest that there is a high association between having skills in analytics and good decision-making, which confirms the proposed theoretical model. Findings provide valuable suggestions for organizations who want to enhance their decision-making process through an analytical approach.

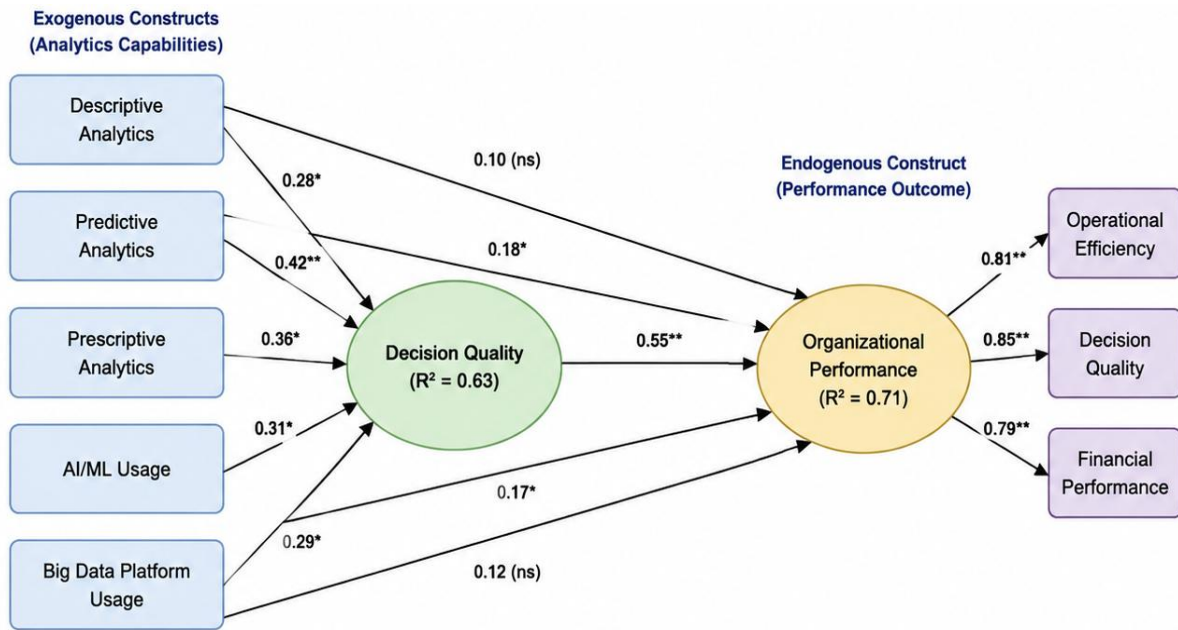


Figure 3: SEM Path Diagram: Impact of Analytics Capabilities on Organisational Performance

Figure 3 represents the effect of the Analytics Capabilities on Decision Quality and Organizational Performance. Positive impacts, represented by solid lines, show that more use of analytics results in better decision-making and organizational performance, and those without any significant impacts are denoted (ns).

Table 2: Regression Analysis

Independent Variable	Coefficient (β)	p-value	Significant?
Descriptive Analytics	0.28	0.05	Yes
Predictive Analytics	0.42	0.001	Yes
Prescriptive Analytics	0.36	0.02	Yes
AI/ML Usage	0.31	0.03	Yes
Big Data Platform Usage	0.29	0.04	Yes

Table 2 illustrates coefficients and levels of significance for the regression of the impact of having analytics capabilities on decision quality. Predictive and prescriptive analytics capabilities have a strong and significant influence on the decision quality.

V. DISCUSSION AND RECOMMENDATIONS

Conclusions reached through the current study confirm that the role of analytics capability is essential in improving decision quality and hence leading to better organisational performance. The effect of predictive and prescriptive analytics and the use of AI/ML applications emerges as more pronounced in influencing managerial decision making compared to descriptive analytics capabilities. This finding agrees with other research on the impact of analytics on improving efficiency and competitive advantage.

Managerial Implications: Organisations need to consider strategic alignment through the linkage between analytics activities and corporate goals. It is imperative to allocate resources towards technologies such as machine learning and artificial intelligence algorithms, predictive and prescriptive approaches, and big data technologies so as to optimally utilize their advantages. Establishing an analytics culture entails the education of managers and employees on how to interpret analytical results, through activities designed with the aim of overcoming organizational resistance.

Issues and Challenges: Even though there are a number of benefits, there may still be several issues that might occur when implementing such technology within organizations. Issues related to data quality and integrity, integration, ethical considerations, and inconsistent use of this technology among other departments might arise. Inconsistent data quality and systems can affect the effectiveness of analytics, while ethical considerations are especially important when handling sensitive data.

Recommendations: Firms are advised to conduct a maturity evaluation in order to know their strengths and weaknesses. They are recommended to undertake a phased adoption process, first predictive analytics and then prescriptive analytics. Employees should receive training on how to use analytics in interpreting information. Data governance should also be undertaken as this will increase the efficiency and effectiveness of the analysis undertaken.

VI. CONCLUSION

The current research offers empirical proof for how analytics capabilities can play an important role in improving decision quality, thereby resulting in improved performance for the organization. As per the regression analysis, Predictive Analytics ($\beta = 0.42$, $p < 0.01$) and Prescriptive Analytics ($\beta = 0.36$, $p < 0.05$) have emerged as two of the most significant factors influencing decision quality. However, Structural Equation Modeling (SEM) results reveal a strong relationship between analytics capabilities and decision quality ($\beta = 0.71$, $p < 0.001$) and decision quality and organizational performance ($\beta = 0.63$, $p < 0.001$). It is also noted that there is a direct impact of analytics capabilities on organizational performance ($\beta = 0.29$, $p < 0.05$). Such results confirm the theoretical assumption that analytics capabilities constitute an important organizational resource that helps to make timely and accurate decisions based on data. From a theoretical perspective, this study is a contribution since it explicates the mechanisms behind better decision-making and organization effectiveness due to the use of analytics. From a practical standpoint, the results help managers determine what steps should be undertaken in order to develop a good decision-making process using analytics capabilities. The limitations associated with the present research involve its cross-sectional nature, relatively small sample of 250 managers from four sectors, and the use of self-reporting surveys. Future research should be conducted using longitudinal designs; cross-sector and cross-country analyses can be used. Additionally, the impact of real-time analytics and edge computing can be studied.

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